Wildfire Danger in the USA: An analysis of the National Fire Danger Rating System

Submitted by Nicholas Walding, to the University of Exeter
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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature: ……………………………………

Abstract:

The United States of America (US) has a long-standing history of fire management through the United States Forest Service. Despite this history of fire management, the US faces significant increases in fire potential across the 21st Century owing to future climate change and due to a legacy of past fuel management policies. Since the 1970s the US Forest Service (USFS) has operated a fire danger rating system, known as the National Fire Danger Rating System (NFDRS), which has aimed to portray, anticipate, and mitigate wildfires across the country. Fire danger ratings essentially aim to describe how dangerous a fire would be if it were to ignite and are used to inform not only the general public about wildfire risk but are also used by forest and fire managers to determine their actions in regards to fire suppression. The US Forest Service's NFDRS currently produces 1-day forecasts of fire danger through the Wildland Fire Assessment System, and other state-focused outlets. The system quantifies common aspects of fire behaviour over wide spatial extents through a number of fire danger indices. These indices represent aspects of fire danger in terms of the likelihood of ignitions, rate of spread, potential heat release, and difficulty of control.

Despite the NFDRS's long-standing utility across the US, relatively few studies have sought to relate fire danger observations and forecasts to records of wildfire activity across its operational spatial extent. The majority of assessments of the NFDRS have been conducted at either single sites or on small spatial scales, despite it being a nation-wide system. This thesis analyses the NFDRS in respect to the occurrence of wildland fires and the final fire sizes they attain over an eight year period (2006-2013) through a number of analyses

that; (i) examine the system's ability to portray wildfire activity across the conterminous US; (ii) assess the NFDRS 1-day forecast's accuracy; (iii) explore the impact of forecasting inaccuracy on wildfire activity across the conterminous US; and (iv) ascertain what outputs from the NFDRS relate most strongly to the formation of large wildfires.

Firstly, this thesis shows that different regions of the US display different levels of correspondence between each observed fire danger indices and recorded fire activity. Areas in the Southern and Eastern Geographic Area Coordination Centers (GACCs) exhibit weaker correlations than those in the Northwest, Northern Rockies, Great Basin and Northern California GACCs. Peaks in fire occurrence are shown to occur at mid–low values of fire danger whereas final fire sizes increase monotonically with each fire danger index.

Secondly, it is shown that the 1-day NFDRS forecasts have a strong correspondence with observed fire danger indices across the USA in the majority of locations. However, it is clear that there are multiple instances when these 1-day forecasts either over- or under-predict fire danger conditions, where there is systematic over-prediction of low-end fire danger values and under-prediction of high-end fire danger values. These predictive errors likely stem from errors in forecasted fire weather conditions, the subsequent derived fuel state and the reporting time of daily observations.

Thirdly, when the inaccuracy of these forecasts was assessed spatially and temporally, the regions with the highest percentage of inaccurate forecasts were found to be in the Northern Rockies and Great Basin Geographic Area

Coordination Centers (GACCs). Over-prediction was found to mainly occur between February and May, whilst peaks in the under-prediction of fire danger were found to be in spring and late summer.

Finally, large wildfires appear to occur when fire danger indices are highly variable throughout the lifetime of a fire. As such this highlights the importance of considering daily variations in specific fire danger indices and that current understanding of variable fire danger conditions does not allow for the near-term prediction of large wildfire potential.

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List of Abbreviations:

BD – Burning Duration

BI – Burning Index

BP – Burning Period

DOC – Date of Containment

DOD – Date of Discovery

ERC – Energy Release Component

FA – Wildfire Activity

FC – Fire Cause

FDI(s) – Fire Danger Index (or indices)

FDR – Fire Danger Rating

FDRA – Fire Danger Rating Area

FE – Fire Event

FFS – Final Fire Size

FO – Fire Occurrence

FPA FOD – Fire Program Analysis Fire Occurrence Database

FSC – Fire Size Class

FSE – Fire Science Exchange

GACC(s) – Geographic Area Coordinating Center(s)

GCM – Global Circulation Model

GSI – Growing Season Index

IC – Ignition Component

JAS – July, August, September

KBDI – Keetch-Byram Drought Index

LST – Local Standard Time

LWFs – Large Wildfires

MAM – March, April, May

NFDRS – National Fire Danger Rating System

NIFC – National Interagency Fire Center

NWCG – National Wildfire Coordinating Group

NWS – National Weather Service

PC – Principal Component

PCA(s) – Principal Component Analysis (Analyses)

PWS – Predictive Weather Service

RAWS – Remote Automated Weather Station

s.e. – standard error

SC – Spread Component

SD – standard deviation

STL – Staffing Level

USFS – United States Forest Service

VLFs – Very Large Wildfires

WFAS – Wildland Fire Assessment System

WIMS – Weather Information Management System

WS – Weather Station

WUI – Wildland Urban Interface

“I’ve known people with exceptional talent – and some have wasted it. Ambition spurs a man on.”

Geoffrey Boycott

Chapter 1: Introduction

1.1. History and Drivers of Wildland Fire

Wildfire is the most ubiquitous natural disturbance across the globe (Belcher et al. 2010) with a current global burned area of 3.0–3.8 million km^2 (Giglio et al. 2013, Alonso-Canas and Chuvieco, 2015). However, wildfires are a natural phenomenon that are a key component of the Earth system. Wildfires have occurred on Earth for the past 410 million years, as evidenced by the first finds of fossil charcoal in the geological record (Glasspool et al. 2004). Throughout this long time span, fire has shaped the planet's vegetation by altering vegetation composition and even driving evolutionary innovations in plant groups such that some plant lineages have become adapted to fire (see Belcher et al. 2013 for a review). As such, ecosystems now exist that are both fire-dependant, and fire-adapted. Such innovations and interactions with fire have created flammable ecosystems (where flammability refers to the ability of a chemical to burn or ignite, causing fire or combustion) such as savannah grassland in climate zones where otherwise climax plant communities would exist given just climate or soil factors (Pausas and Keeley, 2009). In an increasingly human-dominated environment, despite fires long history on our planet and relationship to natural ecosystems, wildfires pose significant challenges to society (Bowman et al. 2009) through the inherent damage and risk they pose when human populations are brought into contact with them.

Wildfires are driven by a number of natural factors such as temperature, precipitation, wind, humidity, fuel availability, and the location of lightning strikes (Westerling et al. 2003). Different combinations of factors play different roles in their influence on fires across a multitude of scales, both temporally and spatially. These scales can range from conditions in a specific forest stand on a certain day to seasonal outlooks for an entire ecoregion. Moreover, location is a key factor when understanding what variables affect wildfires as different regions can be dominated by regional-climatic or vegetative phenomena that directly affect and respond to wildfires. Therefore building an understanding of wildfires requires an appreciation of the diversity of different fire systems present across the globe.

Meteorological variables (both on the scales of climate and weather), topography, and fuel characteristics influence and determine the propagation of fire and its behaviour. For instance, climatic and meteorological conditions influence the ignition and development of fires (Benson et al. 2009) where solar radiation, air temperature and relative humidity affect ignition and propagation of fires (Planas and Pastor, 2013). It is argued that wind has the greatest effect on fire spread and fire intensity through its direct effect on the combustion reaction (Albini, 1982, Beer 1991, Taylor et al. 2004, Sullivan and Ball, 2012).

Topography significantly influences fire behaviour through a direct effect on fire propagation but also indirectly through affecting fuel properties. The aspect of terrain can create shading effects, which can cause microclimates and maintain high fuel moistures, which can alter fire behaviour significantly (Holden and Jolly, 2011). Slope angle, however, has the greatest influence, especially when coupled with wind as when a fire spreads upslope it causes the flame tilt therefore lengthening the flames and subsequently increases the spread of the fire (Pyne et al. 1996, Sharples, 2008).

Fuel characteristics are key determinants of fire behaviour where both physical and chemical properties of fuel determine the probability of ignition and fire behaviour. Fuel characteristics are important across scales and both micro and macro scale fuel properties influence fire. The micro-scale properties include the morphology of fuel particles and lignin and terpene contents for example (Dewhirst and Belcher, *in review*). For example fuels with different volatile contents (e.g. terpenes) directly affect the intrinsic flammability of fuels whilst particle size influences ignition and propagation where smaller fuel particles have higher surface-to-volume ratios and therefore tend dry fasters and be more readily ignitable. Macro-scale structural properties include the packing orientation and packing density of fuel beds and influence the amount of aeration in the fuel complex. Lower bulk densities promote air entrainment, which dries fuel particles and therefore enhances fire propagation (Nelson et al. 2011). Moreover, canopy bulk density and fuel continuity, as well as fuel load have strong influences on fire intensity and spread. The presence of uniform and continuous horizontal fuels (dead woody fuels, litter and duff) greatly enhances fire propagation. If this is coupled with continuity with vertically arranged fuels (live grasses, shrubs and trees) through ladder fuels, the fire can transition from surface vegetation fires into the canopy, causing further changes to fire behaviour in the crown fires (Cruz and Alexander, 2010, Alexander and Cruz, 2011).

Favourable concurrent fire weather and long term-antecedent climatic conditions lead to favourable fuel loads and fire spread conditions (Riley et al. 2013, Stavros et al. 2014) which in turn increase the potential for more devastating wildfire events. Fire-conducive fuel conditions relate to higher fuel loads, brought on by a strong preceding-growing season, that are followed by long-term drought conditions that provide large amounts of cured fuel susceptible to ignition and fire spread (Keeley and Rundel, 2005). This highlights that both short-term and longer-term climatic variables and fuel characteristics greatly affect fire behaviour and fire occurrence.

1.2. The Wildfire Problem in the USA

The USA is considered to be one of the global wildfire hotspots (along with Australia, The Mediterranean and Southern Africa) and faces a particular set of challenges focussed around wildfires, vegetation change, climate change, and urban development. This thesis has chosen to focus on the USA because it captures a large latitudinal climate range and hosts many different ecosystems and ecoregions that host a wealth of different fire systems. This means that by studying the US it is possible to capture a broad range of pyrodiversity within a single study. The US also has a long-standing history of fire management through the United States Forest Service (USFS) and is capable of providing long-term records with which to assess how wildfire management practices and wildfires have interacted. Additionally, the importance of the US in terms of future fire activity has been highlighted by Liu, Stanturf, and Goodrick, (2010) where the region has been identified as one where significant increases in fire potential are expected across the 21st Century owing to future climatic change.

The wildfire problem in the US links to three key factors; climatic changes, shifts in fuel load and diversity, and land use changes. Wildfire risk appears to have changed in recent decades when set against the past century of records and are projected to continue to change throughout the first half of the 21st century. Moreover, the economic impact of wildfires is of growing concern due to the lengthening and severity of fire seasons in the USA (Preisler and Westerling, 2006, Flannigan et al. 2013, Jolly et al. 2015a); for example between 2002-2011 wildfires accounted for $13.7 billion in total economic losses and $7.9 billion insured losses which is a significant increase on the previous decade that saw $6.8 billion in total economic losses and $1.7 billion insured losses from wildfires (Lloyd's 2013). However during the 2017 fire season, which saw 71,499 wildfires, 10,026,086 acres burned, and nearly $3 billion spent in federal suppression costs (NIFC, 2018a), two significant wildfire events occurred. The Tubbs fire (northern California) and Thomas fire (southern California) together incurred $14 billion in insured losses, highlighting the growing wildfire threat to human populations. Moreover, so far in the 2018 fire season (as of the 11th May) 20,444 fires have been reported and 1,460,176 acres have been burned (NIFC, 2018a), pointing to the potential for another critical year for fire management agencies and the insurance industry.

Fire regimes in the USA appear to be shifting towards larger, more infrequent fires and this seems to be driving the recent trends in both fire suppression expenditure and insured losses. This has been argued to be in response to both changes in the climate and changes in fuel load dynamics from past fire suppression activities (Meyn et al. 2007) (e.g. total fire suppression policies). Over the last 30 years, global temperatures have increased by ~0.2C per decade (Hansen et al. 2010), leading to the acceleration of the global water cycle which has led to more extremes in rainfall (Trenberth et al. 2003), more severe episodes of drought (Dai, 2013), and variations in regional humidity (Dessler, Zhang, and Yang, 2008). In light of these climatic changes, Jolly et al. (2015a) have shown that between 1979-2013, fire seasons have lengthened in their duration across 25.3% of the Earth's vegetated surface, with an 18.7% increase in the global mean fire season length. In addition to this, the US fire season was 78 days longer on average from 1987-2003 versus the average fire season length from 1970-1986 (Preisler and Westerling, 2006). The occurrence of Very Large Wildfires (VLFs, defined as >5000ha) has also increased in recent years across the USA between 1984-2010, most notably in the south-western and south-eastern USA (Barbero et al. 2014, Dennison et al. 2014).

The impact of future climate change on these factors could have significant ramifications for potential wildfire activity in the future (Pausas et al. 2004, Flannigan et al. 2009). This could result in more fire-conducive conditions, either in fuel conditions or extremes in weather, or the alteration of fire regime dynamics. This can lead to the exacerbation of already significant wildfire impacts, both environmentally and economically. Following recent trends in VLFs, Barbero et al. (2015) have projected future changes in VLF potential across the USA for the mid-21st Century. The greatest increases in VLF potential have been predicted in the Western USA, particularly in Northern California, based on the increased seasonality of atmospheric conditions that are conducive to VLFs (Barbero et al. 2015). The study also stresses the importance of increases in VLF potential in Eastern USA. Even though these increases in potential are of a smaller magnitude than those projected for Western USA, they are of significance owing to the region being more densely populated which could lead to substantial impacts on private property and air quality related health impacts (Barbero et al. 2015).

Future climatic conditions have been predicted to favour more erratic wildfires across the Western USA through the increased number of individual days, and the increased number of consecutive days with high Haines Index values (Luo et al. 2013). The Haines Index characterises dry, unstable air in the lower atmosphere that could contribute to extreme fire behaviours and aid the spread and growth of wildfires (Haines, 1988). The results of Luo et al. (2013) suggest an increasing frequency of days with high risk of rapid wildfire growth. Other predictions of future wildfire activity include an increase of wildfire potential in the USA, particularly in the Southwest, Southeast, Rocky Mountains, Pacific coast, and the northern Great Plains, owing to changes in the Keetch-Byram drought index (KBDI) (Liu, Stanturf, and Goodrick, 2010). Additionally, a temperature-induced increase of 54% in annual burned area is predicted in the Western USA by 2050 (Spracklen et al. 2009). These future predictions in potential wildfire activity across different regions of the USA will pose new threats to both the human and natural environment. These changing threats will require increased resources and management efforts in order to minimize adverse impacts. Therefore understanding the scale of such potential impacts in the future is of great importance.

Climatic changes are not the only driver of changes in fire risk across the US, historic management practices and forestry practices have altered fuel conditions across the county. Where large build ups of dense understory fuels have changed fuel loads dramatically and have been argued to be somewhat responsible for the recent dramatic increases in large uncontrollable wildfires (Barbero et al 2015). These increases in fuel loads are suggested to be response to a combination of precipitation effects and historic fire suppression activities. Wildfire management policies from the early 20th Century focused on the immediate suppression of all wildfires, effectively excluding wildfires from the environment (Stephens and Ruth, 2005). Over time however, these practices have led to the unintended consequence of the gradual build-up of forest fuels (Miller et al. 2009) with vast landscapes becoming more combustible as a result of being left unattended or managed incorrectly (Pyne et al. 2008). These fuels are now highly fire conducive in light of recent and predicted climatic change. In a study looking at the contributing factors to the formation of mega-fire events, Williams, (2013) found that elements such as; fire exclusion, land management decisions resulting in dense forest conditions with high biomass, and fuel build ups over extensive areas, were consistent across the majority of mega-fire events featured in the study. Compounding these high-level fuel conditions with extensive periods of droughts over a vast homogenous area results in the greatest mega-fire potential (Williams, 2013). Moreover, Marlon et al. (2012) highlight that contemporary fire exclusion and suppression activities are taking place under warmer and drier conditions than those experienced in previous periods of time that experienced high fire activity and so questions their long term efficacy. As such a range of factors has resulted in a major shift in fire regime dynamics in the USA which is believed to be a strong contributor to the catastrophic wildfire seasons experienced in recent years.

These trends are of stark importance due to VLFs influence on suppression expenditure, economic losses and human health impacts through air quality impacts. However the size of wildfires isn’t the only factor to consider when looking at their range of impacts. From a human perspective of risk, as well as understanding the changing hazard component, one must also consider the (changing-) contexts of the human aspects of the disaster-risk equation (Wisner et al. 2004). Further to this it has been noted that the proximity of fires to urbanized locations or residential communities is also key to determining the severity of their impacts (Syphard et al. 2012). Therefore changes in land-use patterns and the location of human values-at-risk will further change the contexts in which wildfires impact communities, and put ever increasing pressure on fire management agencies. More than 4.5 million US households across the country are at high or extreme risk from wildfires with California (2.0 million households) having the most households exposed to these levels of risk (Verisk Wildfire Risk Analysis 2013, cited in Insurance Information Institute 2015). Furthermore in the 13 states across the western US, 1.2 million residential properties (with a combined value estimate of $189 billion) are currently exposed to a high or very high risk of wildfire damage (Corelogic, 2013).

According to Bowman et al. (2009), shifts in land-use have continued to place more people and property within fire-prone regions. This is most prevalent within the Wildland Urban Interface (WUI). The WUI is a central focus of wildland fire policy and management following the increasingly more severe fire seasons experienced in recent decades, and due to the increasing housing trend within the WUI and more broadly across the USA (Stewart et al. 2007). WUI definitions have evolved over time with no single-operational definition being established. However all definitions have consistently referred to levels of human presence, wildland vegetation, and the notion of a distance that represents the potential for the effects to extend beyond boundaries and impact neighbouring lands (Stewart et al. 2007). According to Radeloff et al. (2005) the WUI is simply the region where houses meet or intermingle with undeveloped wildland vegetation. The WUI in the USA expanded by 19% during the 1990s and in 2000 covered 719, 156 km^2 (9.4% of the land area), and contained 44, 348, 628 housing units, representing 38% of all housing in the lower 48 US states (Radeloff et al. 2005, Hammer, Stewart and Radeloff, 2009). The expansion of the WUI places more people, property, and infrastructure at risk to wildfires. According to Thomas and Butry, (2014), 7.8 million structures, consisting of residential, commercial, industrial, governmental and religious buildings, at a value estimated at $1.9 trillion were within fire-threated areas of the WUI in the first decade of the 21st Century. Owing to recent growth trends and the high amount of values at risk, an increasing trend of economic losses would be expected, but coupled with the predicted impacts of climate change on fire activity (Bowman et al. 2009); the expected losses could be even greater.

A comprehensive study of the WUI and wildfire threat from 2000-2010 by Thomas and Butry, (2014), has highlighted a number of key regions and statistics pertaining to the threat-status of the WUI in the USA. Firstly at a national scale, 17.5 million people reside within the threatened WUI, which itself represented 44.9% of the total extent of the WUI. Of the total 7.8 million buildings located within the threatened areas of the WUI, 93.3% are residential buildings. This represents a combined economic value of buildings and content to $1.4 trillion therefore stressing the importance and exposure of this building type to wildfires. The states with the highest populations at threat all reside within the south of the county and include; California, Florida, Georgia, North Carolina, Texas, and Alabama. Moreover, of the total number of residential properties at threat to wildfires, 54% of them are found in these 6 states (Thomas and Butry, 2014), further stressing their economic exposure and importance as far as land management resources and priorities are concerned.

Furthermore, current relationships between the WUI and wildfire impacts are starting to be reported. For instance, suppression expenditure costs are found to be strongly related to the location and number of residential properties with a doubling of households being associated with a 7% increase in fire suppression costs (Gude et al. 2013). Moreover, from this study there appears to be a threshold in the size of increase in household numbers that results in the greatest increase in suppression expenditure. For instance, an increase from 10 to 20 properties result in a greater increase in fire suppression cost than if 1010 properties increased to 1020 (Gude et al. 2013). Moreover, Syphard et al. (2012), found that the arrangement and location of properties were two factors that strongly contributed to their susceptibility to wildfire. Other findings include that property loss was most likely at low to intermediate building densities, and that the rate of property loss was higher when structures were surrounded by dense, high-biomass fuel loads (Syphard et al. 2012). Given current trends in the development and expansion of the WUI, and the relationships between the

WUI and wildfire risk, future development in these fire prone ecosystems could further exacerbate current levels of exposure to wildfires as well as create new areas at risk.

By 2000 the WUI expanded by over 52% when compared to 1970, and is expected to expand further by 10.3% by 2030 (Theobald and Romme, 2007). Moreover, Theobald, (2005), notes the changes in housing density proportions in developable land across the USA. The results from this study indicate a significant trend of exurban growth, which appears at the expense of less developed land. The exurban housing density class, defined as 0.69-16.18ha/unit, is modelled to represent 12.2% of developable land in 1980 and by 2020 represent 19.6%. This trend is in conjunction with reductions of the rural housing density classes from 86.1% of developable land to 75.2% over the same time period (Theobald, 2005). Exurban growth represents growth beyond the fringes of the urban and suburban development and appears to represent the broad region in which the WUI meets both the rural and urban boundary. Housing developments into previously undeveloped areas has mainly been due to urban sprawl and desires to escape urban centres (Stewart et al. 2007). It should be noted that the best means by which to measure landscape changes is by assessing changes in housing densities rather than population density or demographic changes (Theobald, 2005). This is owing to the increasing prevalence of seasonal occupancies with the percentage of WUI homes in Western USA that are seasonally occupied ranging from 8% in Washington to 44% in Wyoming (Gude et al. 2008). Therefore, even though populations may be ‘low’ the realised economic values at risk may be greater than population levels may suggest. Owing to this studies such as Theobald, (2005), and

Theobald and Romme, (2007), have focused on how housing density class shifts.

With regards to wildfire studies and risk, some studies have started to look at the impact that climate change and land use change have on wildfire risk, both in separation and in conjunction. Firstly, Westerling and Bryant, (2008) explored the impact of future climate projections on wildfire risk in California using four climate scenarios for three periods of the 21st Century; 2005-2034, 2035-2064, and 2070-2099. The study found that increased temperatures promoted greater large fire frequency in wetter, forested areas due to the impacts on fuel flammability (Westerling and Bryant, 2008). Additionally, estimates of derived-property damage were calculated from 2000 census data. The greatest increases in property damage were found to be in the WUI near major urban areas (Westerling and Bryant, 2008). Building on the work from Westerling and Bryant, (2008), Westerling et al. (2011), and Bryant and Westerling, (2014) combined climate change projections and growth scenarios (which forced land use change) to further estimate changes in wildfire risk in California. Westerling et al. (2011) modelled large wildfire burned area for three 30-year periods of the 21st Century, centred on 2030, 2050, and 2085. Two IPCC scenarios were used, A2 and B2, across 3 Global Circulation Models (GCMs). The largest predicted increases in burned area were from the A2 emission scenario and increases continued through each time period, ranging from 36-74% by 2085 (Westerling et al. 2011). Continuing the use of climate change and land-use change in projecting future wildfire risk in California, Bryant and Westerling, (2014) found that the most extreme increases in residential wildfire risk resulted from a combination of a high growth demographic model and the most extreme climate scenarios. Moreover, according to Bryant and Westerling, (2014) by the end of the 21st Century variations across development scenario accounted for more variability in wildfire risk than variations in climate scenario. This highlights the important influence land use change has on human exposure to hazards, and its role as a factor in calculating wildfire risk. This is ever more pertinent with regards to the predicted expansion of the WUI over the course of the 21st Century (Theobald and Romme, 2007).

Climate change, further changes to fuel dynamics, and greater expansion of the WUI will ultimately place more people and property at risk in or adjacent to flammable ecosystems which have the potential to become ever more fire-conducive. The challenges that this will pose will require action from local residents and communities, local, state, and federal land and forest agencies, policy makers, and the insurance industry. Owing to this a means of communicating fire risk both across the country, on various time-horizons that adhere to the needs of each stakeholder, and in a common lexicon is required.

One of the mechanisms for informing the public about fire risk is via the US National Fire Danger Rating System (NFDRS). This informs people living at the WUI and those wishing to spend recreational time in wildlands and national forests of the fire danger in their area. It guides them to be aware of fire risk and also to act accordingly, for example not lighting BBQs in forests when fire danger is predicted to be high. The NFDRS issues a Fire Danger Rating (FDR) on a daily basis across the conterminous US, this information is conveyed through maps of the FDR (Figure 1.1) and also on signage in fire prone regions and at access points to wildland and national forest areas (Figure 1.2). Behind the scenes of this FDR output are other fire danger indices that themselves are utilised by fire and land managers to aid their ability to prepare for and action any occurring fires. As such this system is designed as an information point for the general public and for those that manage and fight wildland fires. This long serving danger rating system dates back to 1972 and along with Smokey Bear (Figure 1.2) and his slogan of “Only You Can Prevent Wildfires” has built a strong community network to deal with communicating and building an understanding of fire risk in the US. As such the development of the NFDRS was a revolutionary system that since the 70s has aimed to portray, anticipate, and mitigate wildfires across the country, the NFDRS is therefore the focus of this thesis, which broadly aims to assess whether NFDRS outputs (forecasts and observations of fire danger) correlate with records of fire activity (fire occurrence and final fire size) and to test its forecasting ability toward mitigating wildfires. The following two chapters will describe the NFDRS and will detail the aims of this research.

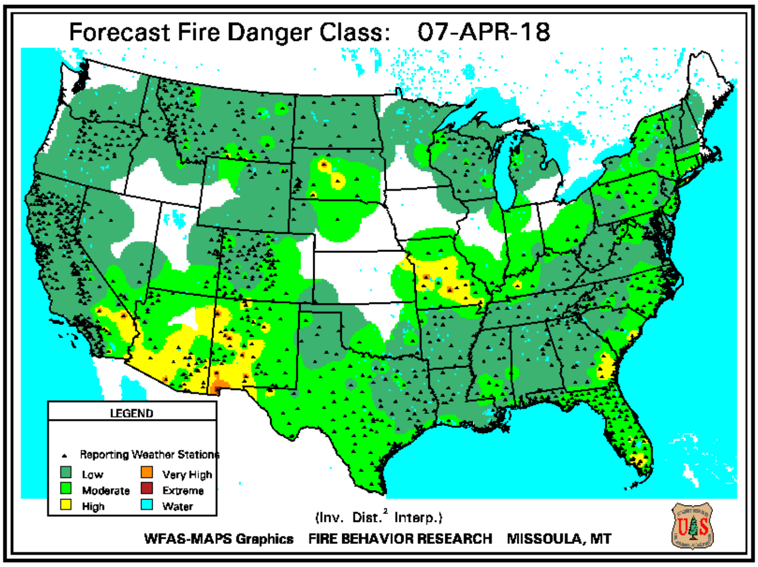


Figure 1.1. Example of a fire danger map released to the public through the Wildland Fire Assessment System website, https://www.wfas.net/archive/www.fs.fed.us/land/wfas/archive/2018/04/06/fd_fcst.png, accessed 14 May 2018.

Figure 1.2. Example of a fire danger rating sign used in national forests across the country to convey fire danger to the public, from http://smokeyzone.com/fire-danger-signs/, accessed 14 May 2018.

“The difference between a score in the 90s and a century is often reflected as the difference between failure and success. It may be illogical, but in cricket, a century has its own magic”

Geoffrey Boycott

Chapter 2: The National Fire Danger Rating System (NFDRS): its history, development, and current utility

2.1. Introduction

The NFDRS, developed through the 20th century, is a computational method that utilises and process local weather input data such as temperature and precipitation with local factors such as fuel type and slope angle to calculate indices that represent different aspects of fire behaviour (Cohen and Deeming 1985). These indices attempt to describe the near-worst current burning conditions in terms of likelihood of ignitions, rate of spread, potential heat release, and difficulty of control (Deeming et al. 1972, 1977). The indices are then used to create a final Fire Danger Rating that, in conjunction with the other indices, facilitates informed fire management decisions and communicates fire danger conditions to the public. Fire danger describes the affect that both constant and variable factors have on the ease of ignition, rate of spread, and difficulty of control of wildfires in an area (Deeming et al. 1972).

‘In summary, fire danger rating is a numeric scaling of the potential over a large area for fires to ignite, spread, and require fire suppression action. It is derived by applying local observations of current or predicted conditions of fuel, weather, and topographic factors to a set of complex science-based equations. The outputs of a fire danger rating system are numeric measures of fire business that provide a tool to assist the fire manager in making the best fire business decisions' (Schlobohm and Brain, 2002, pg. 6).

This chapter will outline and describe the origins of the NFDRS, the rationale behind it, and key points in its ongoing development. The structure of, and scientific background behind the NFDRS will also be explored, as well as details on the multiple intermediate and final indices created to describe different aspects of fire behaviour. Finally, this chapter will propose what aspects of the NFDRS will be examined throughout this thesis in relation to wildfire activity across the conterminous US.

2.2. History, Conception, and Development

The 1910 'big blow-up' was a seminal event in the US and framed the US Forestry Service's agenda on fire for the next50 years. The event and subsequent moderate fire years during the period 1910-1920 caused the agency to see the need for a science based strategy to both explain and predict fire activity in the US. The initial focus was on forests in the western US, west of the continental divide from western Montana across to northern Idaho. This endeavour was in the hope of eventually leading to the opportunity to reduce the number of fires and the size of wildfires. The first forester to be assigned to wildfires was Harry T. Gisborne, Missoula, Montana. Soon he realised the need for a way in which fire managers could communicate in a 'common language' to convey wildfire risk and resource need rather than the loudest of the 'squeaky wheels' receiving most attention and support. Over a period of 8 years, Gisborne quantitatively learned and described the basic influences on fire and their relationships to fire potential and behaviour. Following this the first fire danger meter was produced in 1930, relating fuel moisture, wind velocity, and relative humidity. Although the original tool was highly popular and its principles of a common language of fire danger led to its adoption in several regions outside of the northwest US, it was not long before certain components of the fire danger meter were adapted to suit each of the respective region's specific needs. These localised adaptions to the system however where contrary to the original vision of Gisborne and diminished the current 'common language' of fire danger, which was once again becoming locally nuanced for local needs and applications. Over a period of over 20 years, however, (1931-1954), eight iterations of fire danger meters were produced in the Northern Rockies, each evolving the previous iteration; adding, improving, and removing components through each development.

By 1958, 8 regionally specific variants of the original fire danger rating meters had been implemented across the US (Hardy and Hardy, 2007). At the 1958 national meeting of the American Meteorological Society a truly national fire danger rating system was proposed (Hardy, 1958). This was to facilitate cooperative action between the various agencies, to ensure that increasingly mobile firefighters were able to evaluate burning conditions in terms that were consistent across the US, and to assure that fire prevention warnings had the same meaning to people in all areas of the country (Hardy, 1958). This was to be achieved through the uniform collection of weather data, and through fire danger indices that are based only on common aspects of fire behaviour (such as rate of spread and fireline intensity). Ten years on from the original proposal of a national fire danger rating system, the USFS established the NFDRS research work unit in Fort Collins, Colorado. Prior research, and the pioneering work from Richard Rothermel at Missoula was utilised to create a fire behaviour 'engine' for the NFDRS that aimed to display values of spread and intensity on relative scales of indices (Rothermel 1972, Hardy and Hardy, 2007)

The system was developed and designed to easily incorporate and accommodate new knowledge and was, and still is, modular in nature (Jolly 2018 *pers comm*). At the time of development and implementation, risk was to be evaluated by subjective criteria even though it was recognised that the ultimate preference would be for a purely analytical system based on the physics of heat transfer, fuel moisture, and fire behaviour (Deeming et al. 1972, Hardy and Hardy, 2007). However even with this aim, it is ultimately unattainable as fire manager input and expertise is critical in both the delivery and interpretation of such indices of fire danger.

An operational NFDRS was delivered and implemented nationally in 1972 (Deeming et al. 1972). Figure 2.1 shows the conceptual design of the 1972 NFDRS. It consisted of three levels of inputs; observations (weather variables, 10-hr dead fuel moisture sticks), objective estimates (1-hr and 100-hr dead fuel moistures), and subjective estimates (fuel model, lightning and man-caused risk, slope, woody and herbaceous live fuel moisture). These were inputted to compute 3 primary fire behaviour components; the Spread Component (SC), the Ignition Component (IC), and the Energy Release Component (ERC). The components were then used to derive 3 indices to 'aid planning and supervising fire control activities on a fire protection unit' (Deeming et al 1972). The

Occurrence Index described the potential for fire incidents within a fire danger rating area, the Burning Index (BI) described the potential amount of effort required to contain a fire in a particular fuel type within a rating area, and the Fire Load Index described the total amount of effort required to contain all probable fires occurring within a rating area for a specified period of time. The three indices are normalised to a scale of 0-100. The fire protection unit for NFDRS outputs refers to the Fire Danger Rating Area (FDRA) and represents a geographical area that is best described by a single fire danger station and is relatively homogenous in climate, fuel, and topography (Deeming et al. 1972).

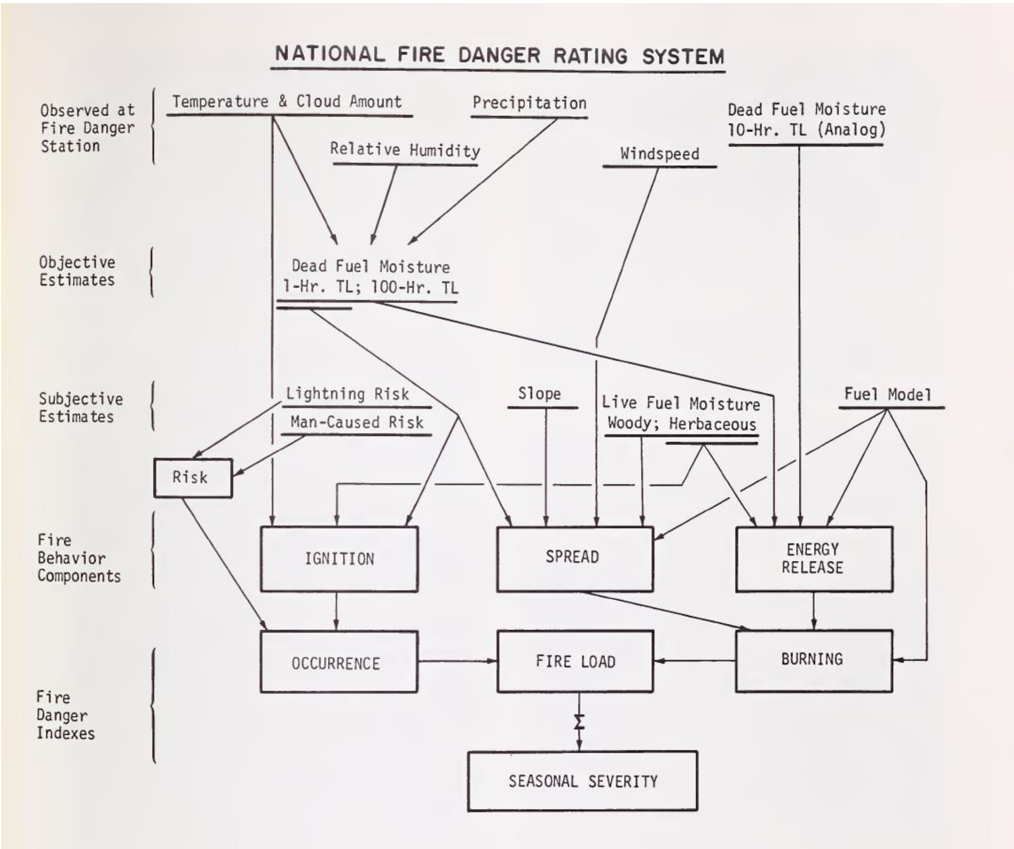


Figure 2.1. Conceptual model of the 1972 NFDRS, from Deeming et al. (1972).

In 1978, the first set of revisions and updates to the NFDRS were employed in response to (Deeming et al. 1977, Bradshaw et al. 1983, Hardy and Hardy, 2007):

- Poor responsiveness to drought
  - This meant the incorporation of a live-vegetation moisture model as well as larger dead fuels. A live fuel moisture model based on seasonal cycles of the 1000-h fuel moisture was also added (Burgan 1979, Hardy and Hardy, 2007).
  - These changes signified a move away from a subjective representation of fuel conditions through herbaceous vegetation transects towards a more analytical and consistent algorithm based on weather parameters – a shift to estimates based on observations or measurements of vegetation phenology.
- A lack of sensitivity in the ratings, especially in low-danger ratings
  - This involved the closed scaling of 0-100 in indices being removed, and the scales becoming open-ended.
- Fuel models not being adequate in representing the range of fuel types in the US
  - More fuel models were added to the system to better represent the range of fuel types, increasing the number of fuel models from 9 to 20.
- Cause of occurrence not being clear
  - This consisted of 2 distinct fire occurrence indices; one for lightning caused, and the second for human caused fires.
- Seasonal changes in the influence of changing day length on the burning conditions

    - This involved representing the ‘drying power’ of the day, and weigh the predicted recovery of moisture content, especially in heavy fuels, by length of day.
- The number of slope classes being too few for mountainous regions
    - The number of slope classes was increased from 3 to 5, with the mid-point of slope class 5 being 90% (number of feet change in height of terrain per 100 feet of horizontal distance).

Following 10 years of operational use, deficiencies in the system were becoming apparent, especially in the eastern US regions. In 1988, a second set of revisions, bespoke to the eastern and south-eastern US, were developed following a special workshop that highlighted the need to mitigate deficiencies as quickly as possible, and to do so without relying on any new, long-term research (Gale et al. 1986). In lieu with the 1978 updates, the 1988 revisions were in line with the original system’s modular design and were quickly slotted into place. The 1988 revisions focussed on 5 key issues (Burgan 1988, Hardy and Hardy, 2007):

- Improved responsiveness to drought in humid environments
    - This mainly focussed on the incorporation of the Keetch Byram Drought Index (KBDI) (Keetch and Byram, 1968, Hardy and Hardy, 2007) into the NFDRS. This drought index is widely used in the south-eastern US and so was both implemented as an individual index, and as a driver of dead fuel availability during drought conditions.

- Provide flexibility to reflect greening and curing of live fuels
  - Based on observations of vegetation greenness, users could enter a season code and a ‘greenness factor’ to better reflect changes in the condition of vegetation than in the previous 1978 version.
- Correct over-rating of fire danger in the autumn
  - These changes provided a smoother transition from spring and summer ‘green’ to later summer/autumn ‘cured’ live vegetation conditions.
- Correct over-rating of fire danger after rainfall events
  - The system had a tendency to under estimate fine dead fuel moistures following rainfall, therefore options in the calculation of fine dead fuel moisture were implemented to avoid this. Additionally, the wind speed reduction factor was modified to better represent hardwood and mixed hardwood-conifer stands in the eastern US.
- Adjust the fuel models to better predict fire danger in humid environments
  - Owing to the previously mentioned revisions to the NFDRS, there was a need to alter each of the 20 fuel models to better represent eastern US fuel types and accommodate the alterations in lieu with humid environments. Therefore in order to provide this for the eastern regions of the US, and provide continuity to the other regions of the US, 20 fuel models representing 1988 revisions of the original 20 models (1978) were added. Users were now able to select from 40 fuel models with each original fuel model having both a 1978 and 1988 version.

2.3. Description of the version of the NFDRS utilised in this thesis

The 1988 revisions were the last set of updates for the NFDRS, and the system has largely been the same since. The following sections will detail key components and aspects of the NFDRS as well as provide a model of the conceptual design of the system.

2.3.1. Basic principles and key assumptions

Fire danger is defined as; 'The resultant descriptor of the combination of both constant and variable factors which affect the initiation, spread and difficulty of control of wildfires on an area' (Deeming et al. 1972). Fire danger is normally expressed in adjective or numeric terms. Producing a fire danger rating involves integrating the effects of existing and expected states of selected fire danger factors into one or more quantitative or qualitative indices that portray a broad area's protection needs (Schlobohm and Brain, 2002). This rating provides a manager a tool with which to assist in the daily operations surrounding 'fire business' in their jurisdiction. The fire danger rating is one part of a fire manager's tool box in making day-to-day operational decisions as they must also rely on their local knowledge of the environment. The fire danger rating, and the other indices produced by the NFDRS, allow the user/ fire manager understand where the current conditions are on the fire danger continuum. The fire danger continuum is the range of possible output values for a fire danger index or component, given a set of parameters and weather inputs from the NFDRS. The continuum allows you to know where along the distribution of values you are currently, whether it be at the ‘cool’ end or ‘hot’ end. Each combination of index/component and fuel model as a unique/individual continuum (or distribution of historic values) for each reporting weather station in the NFDRS network (Figure 2.2, WFAS, 2018a).

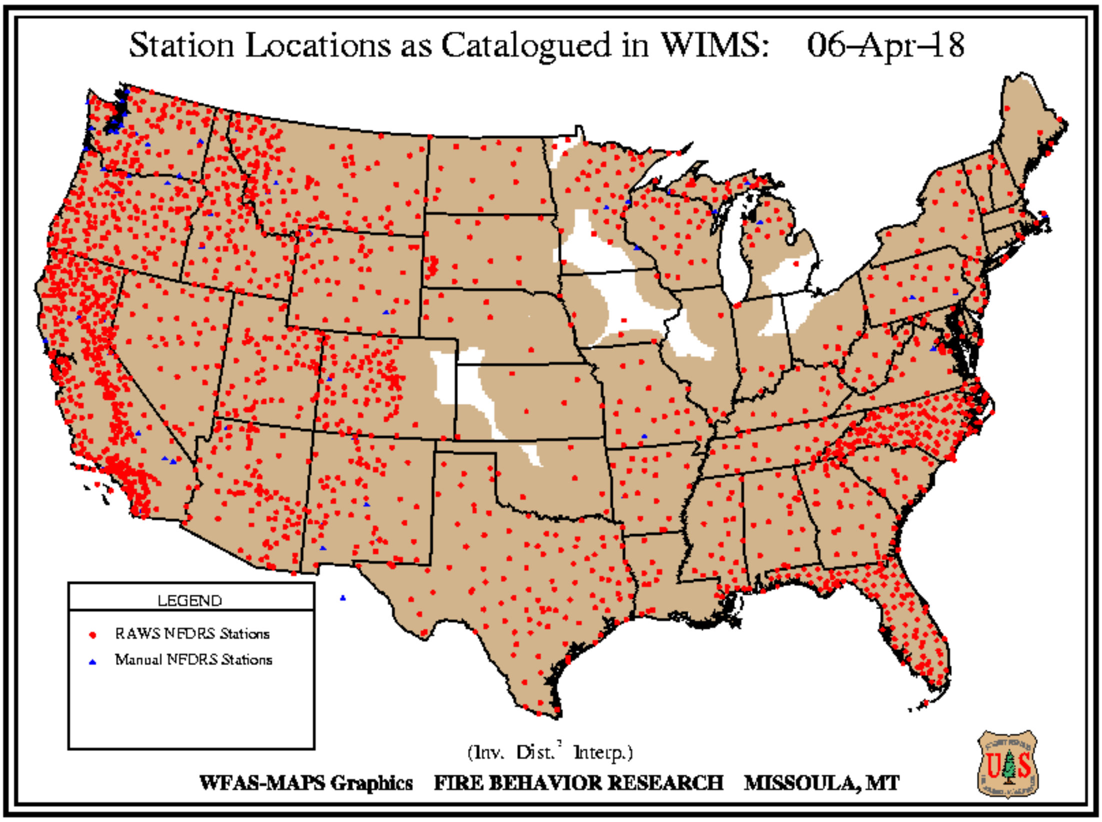


Figure 2.2. Map of NFDRS Weather Stations across the conterminous US (WFAS, 2018a). The beige regions of the map represent the maximum coverage of fire danger information across the conterminous US from the weather stations in the WIMS network. The white areas of the map are areas where there is no fire danger information available.

Fire danger ratings can be calculated in both an observational and predictive manner for fire managers and their respective FDRAs. These FDRAs can span to tens of thousands of acres and therefore fire danger should be considered as a description of the general conditions conducive to fire in terms of ignition, spread, and difficulty of control. It should be noted that even though terminology used in the context of fire danger is similar to that used in the field of fire behaviour, the spatial context of the two fields of science differentiate the two. Fire danger discusses board scale assessments of the conditions whilst fire behaviour focusses on a single fire in a site specific at a specific time.

In order to correctly understand, apply, and interpret outputs from the NFDRS, there are four key assumptions at the basis of the system that need to be understood (Schlobohm and Brain 2002, pg. 6):

1. NFDRS outputs relate only to the potential of an initiating fire, one that spreads, without crowning or spotting, through continuous fuels on a uniform slope.

2. NFDRS outputs address fire activity from a containment standpoint as opposed to full extinguishment.

3. The ratings are relative, not absolute and they are linearly related. In other words if a component or index doubles the work associated with that element doubles.

4. Ratings represent near worst-case conditions measured at exposed locations at or near the peak of the normal burning period.

2.3.2 Structure and processors

The overall structure and framework of the NFDRS can be seen in Figure 2.3. Through this site descriptors, weather observations, intermediate outputs and fire danger indices are inputted and calculated. At 1pm local standard time (LST), daily fire weather observations at each reporting Manual and Remote Automated Wester Station (RAWS) NFDRS station are recorded and reported to the Weather Information Management System (WIMS). Using local descriptors defined by fire managers, fuel moistures and fire danger indices are calculated for each reporting weather station. These calculations are then relayed back to fire managers as well as being fed to the WFAS where, using inverse distance squared interpolation, fire danger maps are produced. 1-day forecasts of fire danger are also produced through the NFDRS where the fire weather observations are sent to the National Weather Service (NWS) and forecasters there apply forecast trends for either specific weather stations or fire weather zones (defined as a group of fire weather stations that experience the same weather change or trend) (Schlobohm and Brain, 2002). The forecasts of fire weather and then sent back to WIMS, where with the same local descriptor defined by the local fire manager, forecasts of fire danger are produced (WFAS, 2018b). The distribution of potentially reporting weather stations is exhibited in Figure 2.2. It should be noted that whilst some weather stations report throughout the year on a daily basis, there are weather stations that only report during the fire season for their particular/local area.

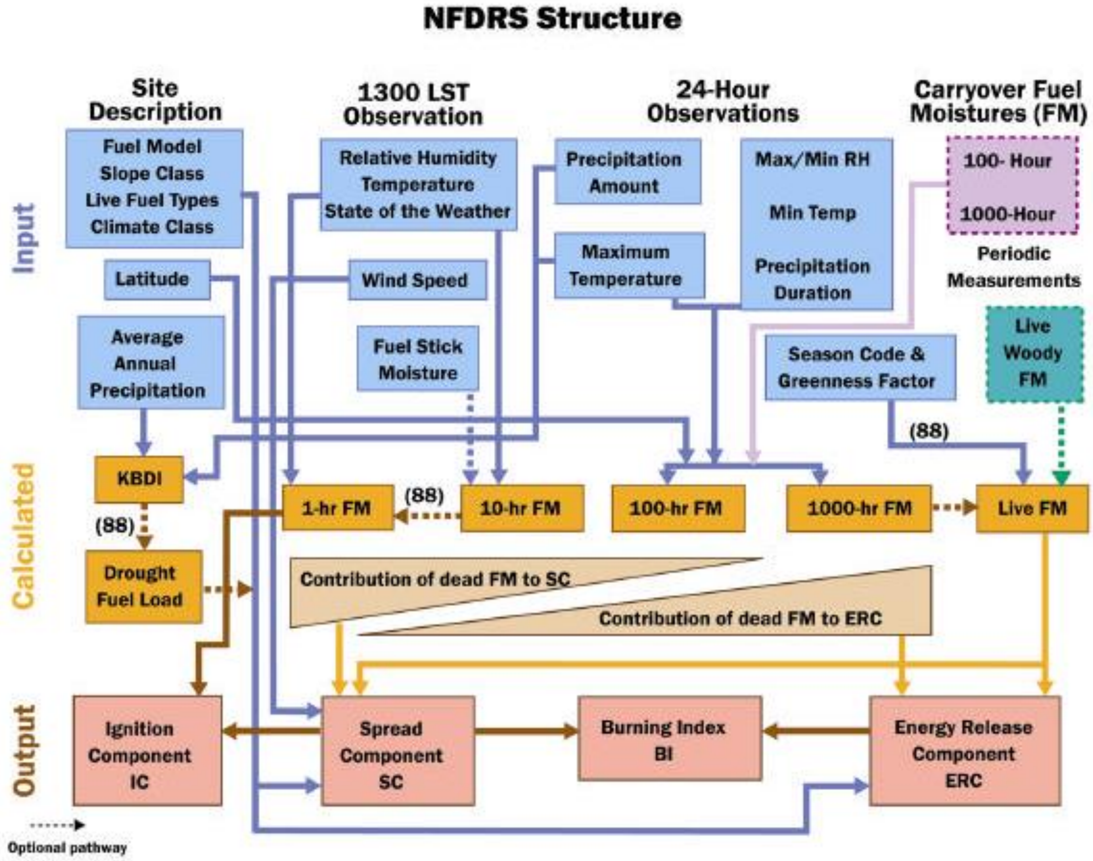


Figure 2.3. Conceptual design of the 1988 NFDRS, the version of the NFDRS analysed in this thesis, from Schlobohm and Brain, (2002, pg. 38).

The fire danger indices (FDIs) presented in Figure 2.3 are then used as the specified staffing index to derive a staffing level. The term 'staffing index' is in reference to the fire danger index selected by the user/fire manager. The staffing index can either be the ERC, the BI, or the SC. Once the staffing index is selected, the staffing level is based on percentile breakpoints in the distribution of the selected FDI for that particular weather station. Where the selected FDI's value lies in the distribution of the FDI's values for that particular weather station will determine the Staffing Level (STL) value. The percentile breakpoints used by the USFS to determine the Staffing Levels is the 90th/97th percentiles whilst other agencies such as the Department of the Interior use the 80th and 95th percentile (NWCG 2011b). Figure 2.4 depicts the fire danger continuum in respect to deriving an STL from to the distribution of ERC values for a particular weather station for which on the day of reporting the ERC has a recorded value of 64.

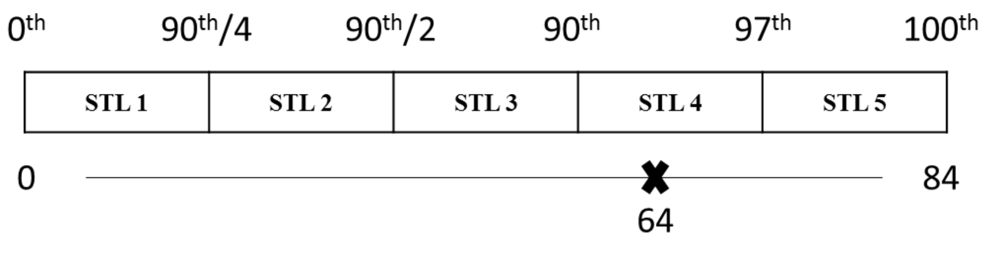


Figure 2.4. Conceptual depiction of the fire danger continuum in respect to deriving an STL from to the distribution of ERC values for a particular weather station for which on the day of reporting the ERC has a recorded value of 64. In this example, the Staffing Index is the ERC.

Using the derived STL and the previously calculated IC, using the fire danger matrix (Figure 2.5) users can derive a final adjective fire danger rating for their respective FDRA or weather station. It should also be noted that up to 4 entries can be inputted through WIMS per station at the discretion of the fire manager and their operational needs, however it is only the first entry that is reported to WFAS for use in the fire danger maps (NWCG 2011a). Each fire danger rating defines a certain set of burning conditions, details of which can be found in Table 2.1.

The next section will describe each of the major data inputs, derived outputs and FDIs in more detail.

Staffing Levels	Adjective Fire Danger Rating				
1-, 1, 1+	L	L	L	M	M
2-, 2, 2+	L	M	M	M	H
3-, 3, 3+	M	M	H	H	VH
4-, 4, 4+	M	H	VH	VH	E
5-, 5, 5+	H	VH	VH	E	E
Ignition Component	0-20	21-45	46-65	66-80	81-100

Figure 2.5. The fire danger matrix; deriving an adjective fire danger rating based on the Staffing Level and Ignition Component values, from National Wildfire Coordinating Group (2011b).

Table 2.1. Definitions of each Adjective Fire Danger Ratings from the National Fire Danger Rating System (NFDRS) (based on Schlobohm and Brain 2002, p. 30)

Fire Danger Rating and Colour Code	**Description**
Low (L) (Green)	Fuels do not ignite readily from small firebrands although a more intense heat source, such as lightning, may start fires in duff or punky wood. Fires in open cured grasslands may burn freely a few hours after rain, but woods fires spread slowly by creeping or smouldering, and burn in irregular fingers. There is little danger of spotting.
Moderate (M) (Blue)	Fires can start from most accidental causes, but with the exception of lightning fires in some areas, the number of starts is generally low. Fires in open cured grasslands will burn briskly and spread rapidly on windy days. Timber fires spread slowly to moderately fast. The average fire is of moderate intensity, although heavy concentrations of fuel, especially draped fuel, may burn hot. Short-distance spotting may occur, but is not persistent. Fires are not likely to become serious and control is relatively easy.
High (H) (Yellow)	All fine dead fuels ignite readily and fires start easily from most causes. Unattended brush and campfires are likely to escape. Fires spread rapidly and short-distance spotting is common. High-intensity burning may develop on slopes or in concentrations of fine fuels. Fires may become serious and their control difficult unless they are attacked successfully while small.
Very High (VH) (Orange)	Fires start easily from all causes and, immediately after ignition, spread rapidly and increase quickly in intensity. Spot fires are a constant danger. Fires burning in light fuels may quickly develop high intensity characteristics such as long-distance spotting and fire whirlwinds when they burn into heavier fuels.
Extreme (E) (Red)	Fires start quickly, spread furiously, and burn intensely. All fires are potentially serious. Development into high intensity burning will usually be faster and occur from smaller fires than in the very high fire danger class. Direct attack is rarely possible and may be dangerous except immediately after ignition. Fires that develop headway in heavy slash or in conifer stands may be unmanageable while the extreme burning condition lasts. Under these conditions the only effective and safe control action is on the flanks until the weather changes or the fuel supply lessens.

2.4. Key components and aspects of the NFDRS

In the NFDRS a lot of variables are considered in the calculation of FDIs, including weather variables and local site descriptors that represent fuel and terrain conditions. These are based on daily observations and the records of observations per weather station as collection continues. The use of fire weather variables leads to the calculations portraying the state of the fuels and longer term weather factors. Finally, all prior variables and components are used in concert to calculate final FDIs and then derive the STL and FDR for a given weather station and FDRA.

2.4.1. Data inputs

Fuel Models – Fuel models in the NFDRS are simulated fuel complexes for which all the fuel descriptors required by the mathematical fire spread model (Rothermel 1972) are supplied. These descriptors include the volume, size, weight, type, depth, surface-to-volume ratio as well as other properties of the fuel bed (Schlobohm and Brain, 2002). There are six general classes of fuel based on the predominant surface fuels; 1) marsh grasses and reeds; 2) lichens and mosses; 3) grasses and forbs; 4) shrubs, 5) brush and tree reproduction; 6) trees; and 7) slash. From these categories, some are broken down to produce 20 different fuel models, each with a 1978 and 1988 version based on the sets of improvements implemented in the 1988 revision of the NFDRS (Burgan 1988, Schlobohm and Brain, 2002). For more details on the individual fuel models, see Appendix II. Figure 2.6 (WFAS, 2018c) shows the static fuel model map of the conterminous US.

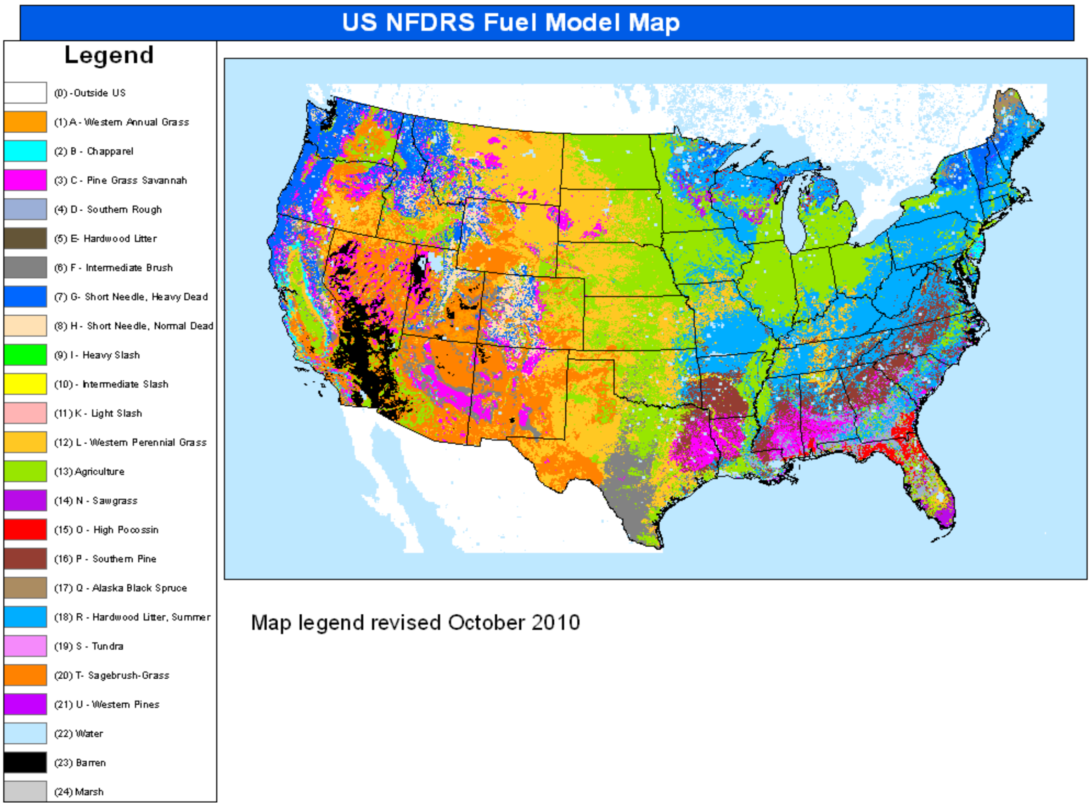


Figure 2.6. Static map of the NFDRS fuel models, Wildland Fire Assessment System (WFAS, 2018c).

Slope Class – Slope represents the rise and fall in terrain in feet per 100 horizontal feet travelled and is expressed as a percentage. The five slope classes used in the NFDRS are: 0-25%, 26-40%, 41-55%, 56-75%, and >75%. The slope class is a key input in the rate of spread calculations used to produce the Spread Component.

Grass Type – The NFDRS recognises the different fuel complexes and loadings owing to the different possible predominant grass types in a FDRA. The distinction is between annual or perennial grasses, where the latter's fuel dynamics is more affected by seasonal weather factors than the former grass type. This results in the drying of herbaceous vegetation is different between these two grass types.

Climate Class – The NFDRS recognises that vegetation adapts to the general climate of the area and that some of these characteristics affect seasonal fire danger. Assigned to each climate class is an assumption on the length of a typical growing season. See Schlobohm and Brian, (2002) for more details.

Annual precipitation – With the addition of the KBDI in the 1988 revisions of the NFDRS, the incorporation of annual precipitation was necessary as the daily relationships between the KBDI and air temperature vary for different levels of annual precipitation.

Weather Inputs – These weather inputs can be either observed (Weather Station measurements) or forecasted (NWS 1-day forecasts based on the weather station observations) based on the fire danger needs of the user/fire manager. The variables necessary for use in the NFDRS are; dry bulb (air) temperature, relative humidity, dew point, wind speed, wind direction, maximum and minimum dry bulb temperature and relative humidity, precipitation amount, precipitation duration, fuels wet flag, and state of the weather (cloudiness/solar radiation). See Schlobohm and Brian, (2002, Appendix V) for more details.

State of Herbaceous Vegetation – State of either the annual or perennial herbaceous vegetation in terms of growing/curing through the year.

Shrub Type Code – Following the 1988 revisions, if users utilise 1988 fuel models in running the system, users must define whether the shrub type is either deciduous or evergreen.

Measured Woody Fuel Moisture – Owing to discrepancies between measured fuel moistures and modelled fuel moistures in the NFDRS (owing to spatial scale and variations), the user has the option to enter measured fuel moistures monthly to aid decision making or to calibrate the woody fuel moisture model if collections are regularly conducted.

Season Codes and Greenness Factors – If the user is selecting 1988 fuel models then these are necessary data inputs. The season code refers to the season of the year the observations are being taken and relates to the various stages of plant development. The greenness factor is necessary for grasses and shrubs indicating how ‘dead’ or ‘flush’ the fuels are.

KBDI Initiation – This needs to be done at the start of each season whether utilising the 1978 (optional) or 1998 fuel models (required). Starting values are typically set at 100, however for more detail on KBDI initialisation see Burgan (1993).

It should be noted that this thesis does not specifically consider these variables directly but they are an intrinsic part of the indices and components that are the focus of this thesis.

*2.4.2. Intermediate output*s

Herbaceous Fuel Moisture – This represents the approximate moisture content of live herbaceous vegetation (expressed as a percentage of the oven dry weight of the sample). The herbaceous vegetation type (annual and perennial) and the climate class are key determinants of the rate of drying in the NFDRS.

Woody Fuel Moisture – This represents the approximate moisture content of live woody vegetation (shrubs, small stems, branches and foliage). This is also expressed as a percentage of the oven dry weight of the sample.

Dead Fuel Moisture (1-hr, 10-hr, 100-hr, 1000-hr, X-1000 hr) – This is the moisture content of dead organic fuels of differing sizes. The key factor driving this is the exposure to environmental conditions present in the FDRA. This moisture content is also expressed as a percentage of the oven dry weight of the sample. The first 4 fuel moisture size classes range from; < one quarter inch in diameter; between one quart and one inch diameter; 1 to 3 inch diameter;

and 3 to 8 inch diameter. The larger the fuel moisture size class, the more long-term fire weather conditions come into play, whilst the smaller fuel moisture size classes are driven by daily weather fluctuations. The X-1000 hr fuel model represents the live fuel moisture recovery time and is derived from the 1000-hr fuel moisture code and is used in the calculation of the herbaceous fuel moisture. In order to ensure stabilised and reasonable values for the 1000-hr and X-1000 hr fuel moistures, weather observations must be started 30-45 days in advance.

2.4.3. Indices and components

<u>Ignition Component</u> – The Ignition Component (IC) represents the probability that a firebrand will cause a fire that will require suppression action. The IC is more than just a probability of ignition and indicates whether the fire has the potential to spread. It is calculated from the Spread Component and the 1-hr Dead Fuel Moisture.

<u>Spread Component</u> – The Spread Component (SC) represents the forward rate of spread of a headfire. Wind speed, slope, Dead Fuel Moisture (1-hr, 10-hr > 100-hr, 1000-hr) and Live Fuel Moisture are used in its calculation.

<u>Energy Release Component</u> – The Energy Release component (ERC) represents the amount of available energy (British Thermal Units, BTU) per unit area within the flaming front at the head of a fire. Dead Fuel Moisture (1-hr, 10-hr < 100-hr, 1000-hr), Live Fuel Moisture, slope, and specific fuel types and fuel models all play an important role in the calculation of the ERC.

Burning Index – The Burning Index (BI) represents the contribution of fire behaviour to the effort of containing a fire. It is derived from the ERC and SC, therefore considers both the rate of spread, and potential intensity of the fire front. The BI however does not relate directly to Flame length, from Fire Behaviour. Instead it relates to the potential flame length in feet, multiplied by 10.

Keetch-Byram Drought Index (KBDI) – The KBDI is a stand-alone index that can be used in the NFDRS to measure the effects of seasonal drought on fire potential. It is fundamental in the use of the 1988 version of the NFDRS and its respective fuel models (Keetch and Byram 1968).

For further details on the indices discussed here, the respective equations for each of the indices can be found in Cohen and Deeming (1985).

2.4.4. The Staffing Level

The Staffing Level (STL) as described above is derived from a selected FDI (or referred to as the Staffing Index) and is based on the daily value of that FDI on the historic distribution of FDI values for that particular weather station. The STL provides an understanding of where the conditions are on the fire danger continuum; the cool end or the hot end, and there is an amount of resources and fire business associated with each STL value (Schlobohm and Brain, 2002).

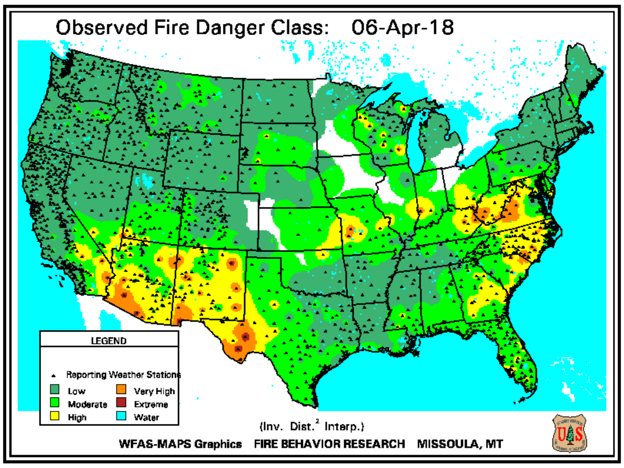
‘The STL can be seen as a required level of ‘readiness’ based on the fire danger conditions being observed and forecast, and is a way of linking fire danger information to fire-management decisions (Schlobohm and Brain 2002). Assigned to each STL are predetermined fire-management actions. This index is predictive in nature as it takes current fire danger conditions (represented by either the ERC, BI or SC) and fuel conditions (represented by the selected fuel model) to inform fire mangers on what appropriate actions are necessary given the fire danger conditions. In the fire danger matrix, Staffing levels are described by numeric values 1–5 (with ± or neutral signs), encompassing the five levels of readiness required at the different ends of the fire danger continuum’ (Walding et al. 2018, pg. 102).

2.4.5. The Fire Danger Rating

The Fire Danger Rating (FDR) represents the way in which fire danger conditions are used in public information releases and fire prevention signing (Schlobohm and Brain, 2002). These ratings bring together all the previous steps in the NFDRS models and convey selected FDIs into a means of communicating wildfire danger. There are five adjective rating categories that represent the different burning conditions along the fire danger continuum. These range from ‘Low’ to ‘Extreme’ and represent the transition from conditions where firebrands do no readily ignite to those where fires spread rapidly and intensely. More details on the 5 categories of fire danger ratings can be seen in Table 2.1. As mentioned above, once a STL is determined (from the selected FDI) and an IC is calculated, using the fire danger matrix, an adjective rating can be deduced and communicated to the public through either national or state focussed outlets.

2.5. Operational applications of the NFDRS outputs

From the structure and processes detailed above, the Wildland Fire Assessment System (WFAS) and other state-focussed outlets deliver information on fire danger. Through these platforms, primarily, maps of fire danger (observed and forecasts for the next day) and the datasheets behind them are provided. Figure 2.7 (WFAS, 2018d) shows an example of the observed fire danger map and data for the 6th April 2018.



06-Apr-18: Fire Weather Observations from WIMS @ 1700 Mountain Time
: Ordered By Stn Id. KBDI= -99 = No Annual Precip for Station / PPT = Observed Precipitation (Inches)

Stn ID	Stn Name	Elev	Lat	Long	Mdl	Tmp	RH	Wind	PPT	ERC	BI	SC	KBDI	HUN	THOU	TEN	STL	ADJ	IC	(Staffing Specs)
*****	Alabama *****																			
10402	BROWNSBORO	529	34.7	-86.3	7G	53	89	2	.22	5	0	0	93	17	21	35	1	L	0	ERC/ 40/ 45/90/97
10702	BANKHEAD NF	989	34.3	87.3	7G	50	100	1	.53	6	0	0	45	19	23	26	1	L	0	BI / 36/ 42/90/97
10990	LIRI	1200	34.4	85.6	8E	57	67	2	.00	23	22	3	693	12	15	13	3	M	4	BI / 30/ 35/90/97
11401	ONEONTA	1104	33.9	-86.3	7G	71	24	5	.00	25	21	3	84	15	21	7	3	M	16	ERC/ 40/ 45/90/97
12201	MOUNTAIN LONGLEAF	1050	33.7	85.7	8G	74	26	4	.00	32	26	4	100	12	20	7	3	M	17	ERC/ 50/ 61/90/97
12302	TERRAPIN CREEK	805	33.8	-85.5	7G	74	23	7	.00	25	28	5	84	16	21	7	3+	M	23	BI / 33/ 39/90/97
12701	TALLGA	600	33.4	86.0	7G	78	21	6	.00	29	30	5	129	15	20	6	3+	M	27	BI / 33/ 39/90/97
12801	SCHOOLHOUSE	932	33.1	86.0	7G	72	23	6	.00	30	30	5	135	13	19	7	3+	M	22	BI / 33/ 39/90/97

Figure 2.7. Examples of an observed fire danger map and the respective datasheet for each of the reporting weather stations, Wildland Fire Assessment System (WFAS, 2018d).

The way in which outputs from the NFDRS are used in fire and resource management decision-making varies between situations and the decisions being made. These range from pre-suppression resource allocation for fire control to prescribed burn planning. The applications of the NFDRS vary/are tailored to the specific decision-making needs of individual fire managers across the country, at a range of scales. Therefore they utilise different combinations of components from the NFDRS and create their own bespoke management plans/procedures. For instance, the majority of units will pre-plan their actions in response to fire incidents (Pre-plan Dispatch Actions). If a fire manager were to have an understanding of how certain indices from the NFDRS were to relate to fire size in that local area, then decisions over the amount of personnel or specialised equipment can be made. Furthermore, the use of NFDRS outputs can strengthen daily briefings on the fire conditions being experienced within a given area. Since 1997, the 'Fire Danger Pocket Card for Fire Fighter Safety' has been a key tool in the firefighters' toolbox (Hardy and Hardy, 2007). Moreover, Public Use Restrictions could be guided by current and forecasted fire danger conditions if there was a known relationship in the local areas between human caused fires and different NFDRS indices. Therefore if an index threshold was exceeded on a given day then public access to national parks could be restricted. On a broader or more regional scale, preparedness levels could be informed by NFDRS outputs. Not to get confused with the STL, preparedness levels are in the sense of coordination of assets and agencies at varying levels based on expected fire activity. This could include bring back off-duty personnel or requesting back-up crews from outside the immediate region. Other forms of support can be through monetary funds that can be accessed in addition to the already assigned funds for fire control actions. This could be awarded based on the comparison of expected seasonal fire danger conditions (represented by NFDRS outputs) with previous fire-years'/seasons' respective conditions. If the expected conditions were seen to be more exceptional, then extra funding could be released. Finally, NFDRS outputs can assist in the use of prescribed burns or in the decision making to allow an ignition to burn under prescribed conditions rather than take suppression actions in light of the potential risk and consequences. Analysing local-historical trends in indices and fire activity can aid in this through the comparison on the current conditions with the average and worst-case burning conditions for a given area.

2.6. Aspects of the NFDRS examined in this thesis

In this thesis I aim to explore the utility of the NFDRS as an operational tool across the conterminous USA in terms of being able to portray different aspects of fire activity. The assessment of fire danger to date has been on either a small scale or at single sites, whilst this thesis will take a wider spatial lens with which to assess the NFDRS.

The aspects of the NFDRS that are of key interest and relevance to this endeavour are those which fire managers use and which translate fire behaviour conditions into actual fire business, the term used to describe the amount of resources and infrastructure needed to cope with concurrent fire activity. Owing to this the first set of analyses will primarily focus on the FDR, STL, and IC. These are the final-stage set of FDIs, and represent fire danger in terms of likelihood of ignitions that require suppression action, the amount of resources and preparedness needed to cope with the current fire-workload, and the overall adjective description of the near-worst case burning conditions. As these final-stage indices are derived from other intermediate components and FDIs such as the SC, ERC, and BI, these indices are also indirectly assessed. They are not just assessed in terms of how well they portray their prescribed area of fire danger but their utility by fire managers and their relevance to fire management in the 21st century is also assessed.

In the final set of analyses presented in this thesis, all 6 of the FDIs calculated in the NFDRS are assessed in terms of their ability to predict/explain/drive the propagation of fires of different sizes, with a focus on large wildfires (>1000 acres). I take this approach in focussing on all indices (FDR, STL, IC, ERC, BI, and SC) in order to ascertain which components and outputs from the NFDRS could have future potential utility beyond their current remit in the prediction of fire size.

“Batting’s all about grafting”

Geoffrey Boycott

Chapter 3: Thesis Aims, Objectives, and Outline

3.1. Aims and Objectives

In light of the challenges the USA may face in the coming years due to wildfires, climate change, fuel changes and WUI development, this thesis aims to assess the National Fire Danger Rating System across the conterminous US in terms of its ability to portray, anticipate, and aid the mitigation of wildfire activity.

In order to achieve this, this thesis will address the following:

1) The majority of previous research has assessed the ability of the National Fire Danger Rating System (NFDRS) to portray fire activity at either single sites or on small spatial scales, despite it being a nation-wide system. The first part of this study will examine the relationships between a set of NFDRS fire danger indices (Fire Danger Ratings, Staffing Level and the Ignition Component) and measures of fire activity (fire occurrence and final fire size) over an 8-year period. In order to assess whether strong correlations exist between reported fire activity and observed fire danger conditions across the entire conterminous US.

2) The accurate prediction of fire danger indices, and their effective communication, are important factors when responding to wildfires and managing fuel levels. The US Forestry Service's NFDRS currently deploys 1-day forecasts of fire danger through the Wildland Fire Assessment System, and other state-focussed outlets. To date there has

been no examination of how accurate these 1-day forecasts are when compared to observed NFDRS fire danger indices across he conterminous US. The second part of this study will assess the accuracy of the 1-day NFDRS fire danger forecasts when compared to the fire danger conditions actually observed for the same days.

3) If clear instances of forecast inaccuracy are established in part 2 of this thesis these inaccurate subsets of forecasting will be compared to records of wildfire activity in order to explore how differing levels of forecasting inaccuracy correspond to concurrent fire activity across the country. The amount of inaccurate forecasting will be examined both spatially and temporally against two metrics of wildfire activity; fire occurrence, and final fire size, in order to identify when and where NFDRS outputs may be found to be inaccurate and how this potentially results in differing levels of fire occurrence or larger final fire sizes.

4) Large wildfires in the USA are of growing concern due to their economic impacts, the suppression costs they incur, and their increasing occurrence in light of recent climate change and historic land-use practices. The final study in this thesis seeks to ascertain which physical and management factors play important roles in the formation of large wildfire events. Two previously unreconciled datasets, the NFDRS data archive and the USFS's Fire Program Analysis Fire Occurrence Database, will be used to form a dataset containing 12,369 fire events that detail the fire danger conditions for every day in each individual fire's lifespan. This will be used to explore whether fire size is merely

dependant on the duration of a fire’s burn period, or whether fire size relates to higher or more variable fire danger conditions occurring throughout a fire’s burn period.

3.2. Data sources and analysis approaches used in this thesis.

In order to achieve the aims and objectives of this thesis, four sets of analyses were conducted and will be presented in the following four chapters. In this section, I will provide an outline of the subsequent chapters that describes the data utilised, the data processing and summarising techniques, and analytical approaches used. By doing so I aim to highlight how the chapters link together and signpost how they are differentiated from one another. Moreover, this section will define the terms utilised in the thesis and provide details on the rationales behind certain methodological and analytical decisions made in the analysis stages of each chapter.

3.2.1. Time period analysed in this thesis

All of the analysis chapters utilise fire danger and fire activity data across the time period 2006-2013. This study period was chosen for a number of reasons. Firstly, at the onset of this study’s inception 2013 was the most recent year that the USFS Fire Program Analysis Fire Occurrence Database (FPA FOD, Short 2014) had published records for. Recently additional data has been released to include records for 2014 and 2015 however, these have not been included as the majority of analyses had already been undertaken. In this thesis the FPA FOD is brought together with the NFDRS archive (WFAS.net/archive). The

NFDRS datasheets are consistently formatted back to 2006 where prior to this the format of the available data is considerably less conducive to good quality analyses. Therefore whilst, the FPA FOD has reliable fire occurrence records that extend back to 1992, the reliability of, and changes to the formatting of the NFDRS datasheets back to that time point led to 2006 being the start point for the analyses presented in this thesis. This provided close to 3000 days of data with each day providing data covering the conterminous USA; that from a computational standpoint, was suitably challenging and of significant resolution to undertake the aims proposed in this thesis.

3.2.2. Data sources and formatting of datasets for analysis

The first three analysis chapters of this thesis (Chapters 4-6) utilise data from the NFDRS archive (WFAS.net/archive) and the USFS Fire Program Analysis Fire Occurrence Database (FPA FOD, Short 2014). In order to relate these two previously unreconciled datasets the data from the two data sources are transposed from data frames and database tables to 3-dimensional grids that represent the US, both spatially and temporally covering the time period 2006-2013 (2922 days, 96 months) such that each day or month can be considered as a page in a flipbook of the conterminous US with fire danger or fire activity data being exhibited in the grid squares. The data from 2006 through to 2013 is spatially summarised at a 1x1 degree spatial resolution throughout the thesis but temporally summarised on both a monthly and daily basis, depending on the analysis being conducted. Each grid square across the conterminous USA has 96 months and 2992 days worth of fire danger and fire activity data, assuming no data gaps in the spatial coverage in the original data sources. The size of the grid squares was chosen to be 1x1 degrees as this scale matches the spatial remit of the fire danger indices, as designed by the NFDRS. If the grid square was to be smaller, this may potentially limit the potential overlap between the fire danger data and fire activity data and thus potentially limit the spatial coverage of the analysis across the US, as well as potentially reduce the statistical significance of the relationships between the two sets of data as less data may be available for analysis. The data prepared in these formats is then used to explore the relationships between fire danger indices from the NFDRS and records of fire activity, and to assess the accuracy of the NFDRS's 1-day forecasts of fire danger and its resulting relationships with fire activity.

The final analysis chapter of this thesis (Chapter 7) utilises the same original datasets from the NFDRS and the USFS FPA FOD however it utilises them in a different way when compared to the previous three analysis chapters. Chapter 7 uses a 3-dimensional grid of fire danger data (latitude, longitude, time), in the same vein as those employed in Chapters 4-6, but the 3-dimensional grids used in Chapter 7 summarises the fire danger data at the daily level, giving 2922 time points per grid square, such that the aforementioned USA 'flipbook' now contains 2922 pages. These fire danger grids were then cross referenced with the fire occurrence records from the USFS FPA FOD where each fire was located in the relevant grid square in the point in time when the fire occurred and was assigned it's relevant fire danger conditions for each day that the fire was burning (based on the date of discovery and date of containment for each individual fire). Each fire was then assigned a fire size class and the fire danger conditions throughout each fire's lifespan was compared across fire size classes in order to ascertain what outputs from the NFDRS might best explain what leads to fires of different sizes, and in particular large wildfires.

See Appendix III for the specific R code used to create the 3-dimensional grids of fire danger (observed and forecasted) and fire activity (fire occurrence and final fire size).

3.2.3. Data Processing, Statistical Analysis, and Generation of Novel Datasets

Chapter 4 assesses whether or not the NFDRS well portrays fire activity across the conterminous US. In order to achieve this, it compares fire danger data from the NFDRS with records of fire occurrence from the USFS FPA FOD. This chapter solely focusses on the observed fire danger indices produced from the NFDRS (i.e. the fire danger that was calculated directly from weather parameters on the day, as opposed to those indices forecasted the day before using National Weather Service weather forecasts) and correlates these with recorded fire occurrence and final fire size (from the FPA FOD). The two sets of data have been spatially summarised at a 1x1 degree grid spatial resolution on a monthly time scale. Monthly means of each fire danger index were produced for each gird square across the conterminous US. The Fire Danger Indices selected for analysis in this chapter were the FDR (the Fire Danger Rating), the STL (the Staffing Level), and the IC (the Ignition Component). Firstly, the FDR, STL, and IC are of particular interested because they are the end-member indices that translate fire danger into critical fire management tools. Secondly, these indices are consistently calculated by the NFDRS RAWS weather stations through the WIMS system whilst, the other outputs and indices such as the SC

(Spread Component), the BI (Burn Index), and the ERC (Energy Release Component) are not always calculated.

Monthly totals of fire occurrence (counts) and final fire size (acres) were calculated for each grid square across the conterminous US and correlated with the monthly means of each fire danger index (FDR, STL, and IC) for every grid square across the conterminous US. Spearman's Rank correlation (a nonparametric measure of rank correlation, the statistical dependence between the rankings of two variables) was utilised as it allows for the correlation of both ordinal and continuous datasets as well as identifying non-linear relationships as it ranks values as appose to having the values unranked. The relationships between the fire danger indices and measures of fire activity were then further explored using percentile trends and moving-means across the fire danger spectrum on a national-scale to explore the relationships between these sets of variables. Tables A4.1 and A4.2 in Appendix IV provide further details on the specific data processing and analysis steps conducted in Chapter 4.

Chapter 5 Builds on Chapter 4 by considering both the forecasted and observed fire danger data from the NFDRS data archive. Firstly, it explores the relationships between the daily-produced forecasted and observed fire danger indices (FDIs) and secondly, explores the relationships between the forecasted FDIs and records of fire activity on a monthly timescale, in accord with the temporal scales of Chapter 4. The term 'forecast' refers to the 1-day forecasts of fire danger produced through the WIMS system on a daily basis for the following day, for each of the reporting NFDRS RAWS weather stations. As with Chapter 4 the FDIs selected for analysis in this chapter are also the FDR, the

STL, and the IC. The observed and forecasted fire danger indices are summarised at a 1x1 degree spatial resolution on a daily timescale, producing daily means for each fire danger index (2922 days across the study period 2006-2013) for the initial stages of analysis in this chapter. The daily means of the forecasted and observed values of each fire danger index (FDR, STL, and IC, respectively) are correlated for 1) every grid square across the conterminous US, and 2) at the national scale (which is all the data from the grid squares across the country amalgamated into one set of data for analysis), to determine the relationships between the observed and forecasted values of each index in order to test the accuracy of the NFDRS forecasts both regionally and for the conterminous US. Spearman’s Rank correlation was employed owing to its ability to correlate ordinal and continuous data.

Once the relationships between the forecasted and observed FDIs was explored. The relationships between the forecasted FDIs and metrics of fire activity were examined. This was achieved following the same methodology as that employed in Chapter 4 allowing the outputs of Chapter 5 to be compared to that of Chapter 4. The forecasted FDIs were therefore summarised once again on a 1x1 degree grid, but this time on a monthly timescale, producing monthly-means of forecasted fire danger indices (FDR, STL, and IC) to be correlated with the monthly totals of fire occurrence and final fire size previously produced in Chapter 4. The monthly-means of each forecasted FDI were correlated, per grid square, with the monthly totals of fire occurrence and final fire size using Spearman’s Rank Correlation and the correlation coefficients produced were contrasted with those produced in Chapter 4 (using the monthly means of the observed FDIs). This was conducted in order to highlight regions across the conterminous US where the forecasted FDIs had weaker relationships with fire activity than the observed FDIs. Tables A5.1 and A5.2 in Appendix V provide further details on the specific data processing and analysis steps conducted in Chapter 5.

Chapter 6 Firstly, considers how the accuracy of the 1-day forecasts of fire danger varies in time and space and secondly, examines how variability in forecasting accuracy of the 1-day forecasts of fire danger relates to fire activity. The daily means of the observed and forecasted FDIs used in Chapter 5 (FDR, STL, and IC) were used to identify instances where the 1-day forecasts were either accurate or inaccurate allowing the forecasted fire danger to be considered as over-, under-, or correctly-predicted when compared to the observed value. In this chapter, the term 'prediction' refers to the relationship between the forecasted and observed index values, with over-prediction indicating that the forecasted value was greater than the observed value, under-prediction indicating when then forecasted value is lower than the observed value, and correct-prediction being when the forecasted value equalled the observed value. Specific details on how these 3 categories are defined according to certain thresholds, and the resulting sub-sets of the forecasted reports, are described and presented in Chapter 6 (Section 6.2.3 and Table 6.1). These 3 populations (over, under, corrected prediction) of forecast accuracy were then used to calculate the percentages of forecasts per month that fell in each population subset, creating monthly-mean percentages of forecasts for each FDI that were over-, under-, or correctly-predicted. This provided a record of forecasting accuracy through the year with the percentage of forecasts that were either over-, under-, or correctly-predicted (12 data points representing each month in the year per FDI per accuracy subset population). This was conducted on both the national scale and per grid square across the conterminous US. In order to couple this data with records of fire activity, the monthly-mean variance in fire occurrence and final fire size (12 data points per metric) were calculated by firstly calculating daily totals of fire occurrence and final fire size for the time period 2006-2013. These were then used to evaluate the daily variance in fire occurrence and final fire size across the eight years. These daily variances were then used to compute the monthly-mean variance in fire occurrence and final fire size for each month of the year both on the national scale and for each grid square across the conterminous US. The monthly-mean percentage of over-, under-, and correctly-predicted forecasted for each FDI were then correlated (Spearman's Rank) with the monthly-mean variance in fire occurrence and final fire size in order to understand the relationship between the forecasting accuracy of the NFDRS and fire activity. This was conducted on both the national scale, all grid squares in aggregate, and for each grid square across the country on a 1x1 degree grid. Tables A6.1 and A6.2 in Appendix VI provide further details on the specific data processing and analysis steps conducted in Chapter 6.

Chapter 7 explores the relationship between the observed fire danger that occurs throughout the lifetime of individual fires and their resulting final fire size. In contrast to the previous chapters, this study utilises all six of the NFDRS FDIs (FDR, STL, IC, SC, BI, and ERC) because rather than analysing outputs from the NFDRS from a management-tool perspective that is already in place and used by fire managers (as was the focus in Chapters 4-6), this analysis intends to instead highlight which of the six FDI outputs best links to determining the size of wildfires, and in particular the FDI conditions that lead to large wildfires. This study therefore differs from the previous three chapters in that it looks at the fire danger during specific individual wildfires whilst the previous chapters looks at the relationships between fire danger and the levels of wildfire activity for a certain area. In order to achieve this the observed FDIs were processed and summarised as daily means on the 1x1 degree grid across the conterminous US, whilst the records of fires from the USFS FPA FOD were retained in their original table format. In order to associate fire danger conditions (i.e. the fire danger index values) with each individual fire I looped through each grid square of the conterminous US and associated the corresponding fire danger data for every fire that burned in a given grid square for the entire duration over which a fire burned. This was achieved using the latitude and longitude data from each fire in the FPA FOD and its dates of discovery and containment in order to pull out the observed fire danger index values present during the days that each fire burned. The daily record of each fire's fire danger was then summarised by the mean and Standard Deviation (SD) of the fire danger index values across the fire's burn period. Therefore, for every fire, mean fire danger and SD in fire danger were calculated for each of the six FDIs, creating twelve variables for each fire. These twelve exploratory variables, as well as the number of days each fire burned for (referred to as the Burn Duration, BD) were examined to explore the relationships between fire danger and fire size. In order to compare fires of different sizes, Fire Size Class definitions were taken from the National Wildfire Coordinating Group of which there are 7 classes (details that are provided in Table 7.1 in Chapter 7). For each of the seven Fire Size Classes (A-G), distributions of the mean and SD of each of the six FDIs during each of the individual fires, as well as the distribution of the number of days fires in each class burned for (BD) was known. These thirteen exploratory variables were then examined, contrasted, and compared in order to understand how the fire danger conditions experienced by fires of different sizes varied and to understand what outputs, as well as the way they are summarised to represent an individual fire, best determines and differentiates the various Fire Size Classes. This was achieved through the use of percentile analysis and Principal Component Analysis. Percentile analysis was conducted in the form of boxplots and significant difference tests in order to understand the distributions of fire danger across the seven FSCs, and the statistical significant difference between the distributions of each FDI (mean and SD). The tests employed were the Wilcoxon and Kolmogorov-Smirnov tests. The Wilcoxon tests is used to determine whether two sample datasets are from the same population. The null hypothesis is that the two samples are from the same population, so finding a p value less than or equal to 0.05 would indicate that the two samples are significantly different from one another. The 2-sample Kolmogorov-Smirnov test determines whether two datasets differ significantly from one-another and provides both a D statistic and a P value. The null hypothesis is that the two datasets are the same. The D statistic indicates the magnitude of difference between the cumulative distributions of the two datasets being tested, whilst the p value indicates whether the datasets differ significantly, therefore a p>0.05 allows for the null hypothesis to be rejected. Owing to the information provided from these two tests they were deemed suitable to analyse the distributions of fire danger conditions across the seven Fire Size Classes. Following this initial analysis, certain variables which had demonstrated relationships with the Fire Size Classes were retained for use in the Principal Component Analysis. Principal

Component Analysis allows the reader to understand variance in datasets and understand the internal structure of data. Orthogonal transformations are used to convert sets of observations into linearly uncorrelated variables referred to principal components. Principal components are made of the original variables of the dataset and are used to account for as much variability in the dataset as possible. Understanding the composition of the different components and how they drive variability across the seven Fire Sze Classes will facilitate the identification of the outputs from the NFDRS that are key in determining which Fire Size Classes will be in. Using the retained variables from the first stages of the analysis, certain variables were shown to be key drivers of large wildfires. Information on how to interpret the outputs produced from the Principal Component Analysis (Figures 7.7-7.8 and Tables 7.4-7.6) can be seen in Table A7.2 in Appendix VII. Principal Component analysis was ultimately used as it allows the reader to understand how different variables drive variability in datasets (and in this case, fires) relative to one another and in combination with the other variables being analysis. Tables A7.1 and A7.2 in Appendix VII provide further details on the specific data processing and analysis steps conducted in this chapter.

The data and methodologies detailed in this chapter are fully described in each respective chapter’s Methodology section however, the summaries presented here serve as a form of roadmap to indicate how this thesis will address its key aims and toward highlighting the important linkages between each of the chapters described forthwith.

“They smile and then they stab (media press/ [REVIEWERS!]) – and they think the next time they come along from comment you are going to forget the wounding things they write and obligingly talk to them”.

Geoffrey Boycott

Chapter 4: A comparison of the US National Fire Danger Rating System (NFDRS) with recorded fire occurrence and final fire size

The research presented in the following chapter has been published as:

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Abstract.

Most previous research has assessed the ability of the National Fire Danger Rating System (NFDRS) to portray fire activity at either single sites or on small spatial scales, despite it being a nation-wide system. This study seeks to examine the relationships between a set of NFDRS fire danger indices (Fire Danger Ratings, Staffing Level and the Ignition Component) and measures of fire activity (fire occurrence and final fire size) across the entire conterminous US over an 8-year period. I reveal that different regions of the US display different levels of correspondence between each of the fire danger indices and recorded fire activity. Areas in the Southern and Eastern Geographic Area Coordination Centers (GACCs) exhibit weaker correlations than those in the Northwest, Northern Rockies, Great Basin and Northern California GACCs.

Peaks in fire occurrence are shown to occur at mid–low values of fire danger whereas final fire sizes increase monotonically with each fire danger index. My findings appear to align with perceived shifts in management practices currently employed across the US and indicate that the ability of the NFDRS to apportion the resources required to combat large fires is in general well developed.

4.1. Introduction

Fire danger indices are employed in multiple countries and fire systems to indicate current conditions of fire risk and behaviour in a manner that is understandable by the public and informative for fire managers. Examples are Australia's McArthur Forest Fire Danger Index or the United States National Fire Danger Rating System (NFDRS), which aim to predict the potential for large fire activity in order to enable fire managers to be better prepared in the future (Schlobohm and Brain, 2002).

The success of fire danger indices is typically evaluated by their ability to accurately portray any fire activity that occurs (Viegas et al. 1999; Andrews et al. 2003; Arpaci et al. 2013). However, capturing fire activity across temporal and spatial dimensions is a difficult challenge. In this study, I analyse the relationships between fire danger ratings, recorded wildfire occurrence and final fire size across the conterminous US. The majority of past assessments of the US NFDRS have been conducted at either small spatial scales or for a single site or area (Andrews et al. 2003; Freeborn et al. 2015), or with a focus on the Western US when correlating NFDRS outputs with records of fire activity

(Roads et al. 2010). However, the NFDRS is a national system and so must be representative of a diverse number of biomes, ecological systems and resulting fire regimes. The implementation of a singular national system arose in the 1950s from the need for a common lexicon of fire danger between fire managers in order to compare diverse regions across large spatial scales and to facilitate the prioritisation of management efforts and limited resources (Hardy and Hardy, 2007). Use of a standard fire danger system across such a vast and diverse area as the US may raise issues with its ability to capture the relationships between fire danger indices and metrics of fire activity for each of these different regions. As such, in this study I attempt to quantify the performance of the NFDRS at the national-scale across the US.

The US NFDRS, developed in the early 20th century, is a computational method that utilises and processes Weather Information Management System (WIMS) weather station input data, such as temperature, precipitation, and wind speed, with local factors, such as fuel type and slope angle, to calculate indices that represent different aspects of fire behaviour (Cohen and Deeming 1985). These indices attempt to describe the worst current-burning conditions in terms of likelihood of ignitions, rate of spread, potential heat release and difficulty of control (Deeming et al. 1972, 1977). The model outputs are used to both facilitate informed-fire management decisions and communicate fire danger conditions to the public. Several indices are produced within the NFDRS with some acting as inputs in the construction of other indices. These indices can then be used with different fuel models as inputs by fire managers to produce a Staffing Level. Where the Staffing Level is derived from percentile breakpoints along the Fire Danger continuum, which allows Fire Mangers to make the appropriate management actions that are designated to each Staffing Level (Schlobohm and Brain 2002; National Wildfire Coordinating Group 2011b). The Staffing Level and another index, the Ignition Component, are then used in the fire danger matrix to determine an Adjective Fire Danger Rating (FDR) (Table 4.1, which defines all abbreviations used in this study) for the respective reporting station and Fire Danger Rating Area (FDRA). The five Adjective Rating categories represent different burning conditions along the fire danger continuum and range from ‘Low’ to ‘Extreme’ describing the transition from conditions where fuels are not readily ignited by small firebrands to fires that start quickly, spreading furiously and burning intensely. These five categories are consistently utilised across the US and have been used since the NFDRS was implemented nationally in 1972 (Hardy and Hardy 2007). The definitions of each FDR category can be seen in Table 4.2. Fire danger indices are linearly related, therefore as a component or index doubles it can be assumed that the potential for fires to ignite, spread and required suppression action doubles (Schlobohm and Brain 2002). For each reporting weather station within the WIMS network (Figure 4.1c), a Fire Manager can input up to four entries for local management purposes (National Wildfire Coordinating Group 2011a). The first of these entries is published on the Wildland Fire Assessment System (WFAS) website (http://www.wfas.net) and are used to create daily-forecast and observed fire danger maps of the US. Their constituent weather and fire danger-datasheets are also released to the public through the WFAS website.

Table 4.1 List of terms referred to in this study with their respective abbreviations, definitions and sources. Although the BI, ERC and SC are not directly analysed in this study, they can be selected by fire managers to calculate the Staffing Level. NFDRS, National Fire Danger Rating System. USFS FPA FOD, United States Forestry Service Fire Program Analysis Fire Occurrence Database (based on Schlobohm and Brain, 2002, National Wildfire Coordinating Group 2011b, and Short, 2014).

Term	Abbreviation	Definition	Analysed directly in this study
Fire Danger Rating	FDR	These describe conditions that reflect the potential, over large areas, for a fire to ignite, spread and require suppression.	Yes
Burning Index	BI	A number related to the contribution of fire behaviour to the effort of containing a fire.	No
Spread Component	SC	A rating of the forward rate of spread of a headfire.	No
Energy Release Component	ERC	A number related to the available energy per unit area within the flaming front at the head of a fire.	No
Staffing Level	STL	The basis for decision support for daily staffing of initial attack resources and other activities; a level of readiness and an indicator of daily preparedness	Yes
Ignition Component	IC	A rating of the probability that a firebrand will cause a fire requiring suppression action.	Yes
Fire Occurrence	FO	The term used in this study to represent the number of fires present for a given location at a particular time, defined by their location (longitude-latitude) and discovery date from the USFS FOD.	Yes
Final Fire Size	FFS	Area within the final perimeter of the fire.	Yes
Fire Danger Index (Indices)	FDI(s)	The collective term utilised in this study to refer to the selected NFDRS indices and components used here; the FDR, STL, and IC.	Yes

Table 4.2. Definitions of each Adjective Fire Danger Ratings from the National Fire Danger Rating System (NFDRS) (based on Schlobohm and Brain 2002, p. 30).

Fire Danger Rating and Colour Code	**Description**
Low (L) (Green)	Fuels do not ignite readily from small firebrands although a more intense heat source, such as lightning, may start fires in duff or punky wood. Fires in open cured grasslands may burn freely a few hours after rain, but woods fires spread slowly by creeping or smouldering, and burn in irregular fingers. There is little danger of spotting.
Moderate (M) (Blue)	Fires can start from most accidental causes, but with the exception of lightning fires in some areas, the number of starts is generally low. Fires in open cured grasslands will burn briskly and spread rapidly on windy days. Timber fires spread slowly to moderately fast. The average fire is of moderate intensity, although heavy concentrations of fuel, especially draped fuel, may burn hot. Short-distance spotting may occur, but is not persistent. Fires are not likely to become serious and control is relatively easy.
High (H) (Yellow)	All fine dead fuels ignite readily and fires start easily from most causes. Unattended brush and campfires are likely to escape. Fires spread rapidly and short-distance spotting is common. High-intensity burning may develop on slopes or in concentrations of fine fuels. Fires may become serious and their control difficult unless they are attacked successfully while small.
Very High (VH) (Orange)	Fires start easily from all causes and, immediately after ignition, spread rapidly and increase quickly in intensity. Spot fires are a constant danger. Fires burning in light fuels may quickly develop high intensity characteristics such as long-distance spotting and fire whirlwinds when they burn into heavier fuels.
Extreme (E) (Red)	Fires start quickly, spread furiously, and burn intensely. All fires are potentially serious. Development into high intensity burning will usually be faster and occur from smaller fires than in the very high fire danger class. Direct attack is rarely possible and may be dangerous except immediately after ignition. Fires that develop headway in heavy slash or in conifer stands may be unmanageable while the extreme burning condition lasts. Under these conditions the only effective and safe control action is on the flanks until the weather changes or the fuel supply lessens.

Based on the use of NFDRS indices by US fire managers, fire activity metrics are typically limited to either the number of newly discovered fires or their final fire size (Andrews and Bradshaw 1997). Final fire size, defined here as the area within the final perimeter of the fire (Short 2014), gives an indication as to whether a fire escaped initial attempts of suppression, rather than just a measure of the extent of the total burned area (Freeborn et al. 2015). The relationships between fire danger indices, the number of newly discovered fires and their final fire size are ultimately used to inform fire-management decisions, such as fire prevention, and pre-suppression planning and prioritisation (Schlobohm and Brain, 2002). In recent years, pressure on fire-management administrations has risen because of ever-increasing expenditure on wildfire suppression (Calkin et al. 2005). This recent shift appears to be due to changes in fire regime (the frequency, seasonality, severity, and intensity of wildfires in a specific area over long periods of time, Bond and Keeley, 2005) and fire season length (Jolly et al. 2015a) as a result of recent climatic changes (Barbero et al. 2014, Dennison et al. 2014) and shifts in vegetation dynamics from historic suppression policy (Andrews et al. 2003). This has resulted in an increasing number of large wildfires, and because of their economic, ecological and social impacts, evaluations of the NFDRS have been suggested (Freeborn et al. 2015). Previous assessments have focussed on either the probability of large wildfire occurrence (Preisler et al. 2004, 2008) or the number of large wildfires (Preisler et al. 2008, 2009, Riley et al. 2013, Barbero et al. 2014, Barbero et al. 2015) using different thresholds of burned area to define large wildfires. When conflating burned area with fire danger indices issues arise with summarising fire danger data temporally, as total burned areas are established over long burn periods (Freeborn et al. 2015). Daily indices lose their ability to capture these relationships accurately as a small number of high fire spread days may be responsible for the majority of a fire's extent (Podur and Wotton, 2011, Freeborn et al. 2015). In this sense, relating final fire sizes with fire danger indices over longer temporal windows, as I do here, may be more appropriate than total burned area (Freeborn et al. 2015). In order to improve this I analyse the relationships between the observed fire danger rating from the NFDRS and its component indices with recorded fire occurrence and final fire size across the US, allowing us to consider whether the fire danger indices perform well at capturing fire occurrence and final fires size across the conterminous US.

4.2. Methods

Monthly-mean observed fire danger indices, monthly-total fire occurrences and monthly-total final fire sizes are calculated from daily reports for 1 × 1° grid squares across the conterminous US in order to map spatial and temporal patterns from 2006 to the end of 2013 (Figures 4.1, 4.2). Each of the chosen fire danger indices (Table 4.1) is then correlated over the time period with fire occurrence and final fire size for each grid square in order to assess how and whether these metrics relate well to recorded fire activity.

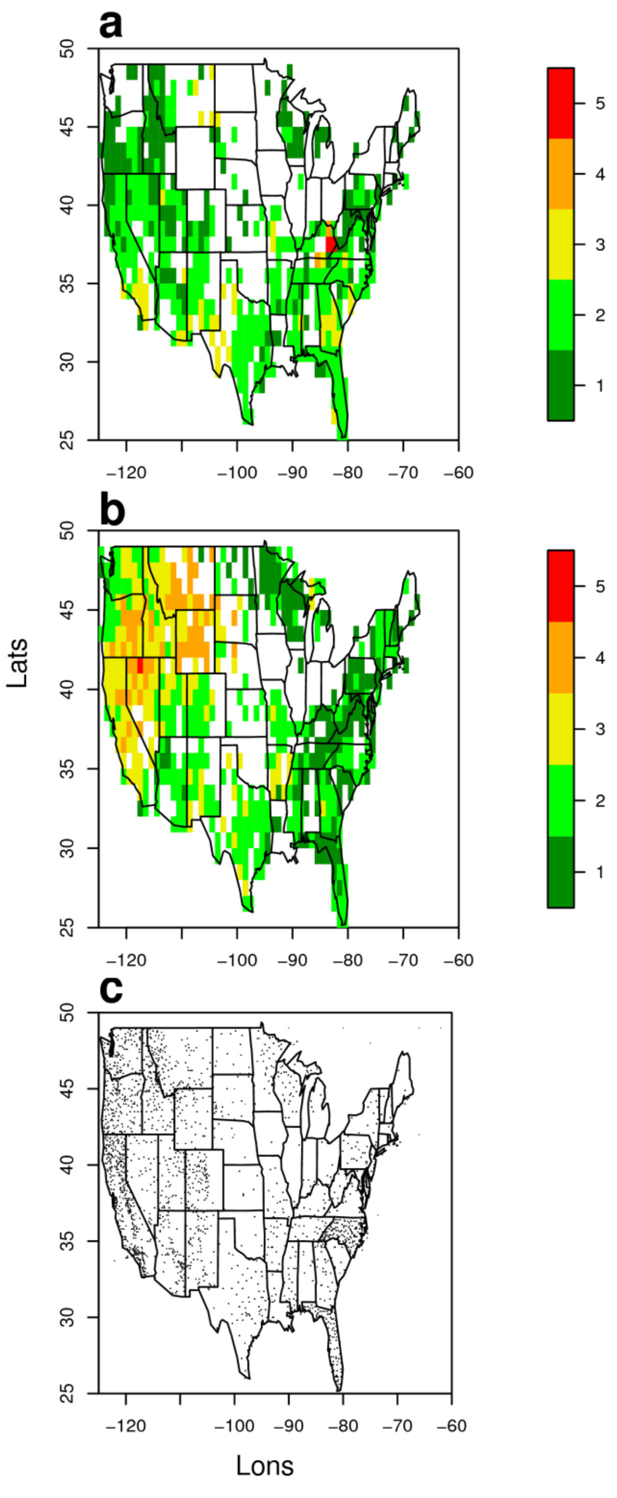

Figure 4.1. Observed monthly mean Fire Danger Ratings (FDR) for (a) January 2012 and (b) August 2012 on a 1 × 1° degree grid, with (c) the spatial distribution of Weather Information Management System (WIMS) weather stations which are used to generate National Fire Danger Rating System (NFDRS) outputs. Values of 1–5 correspond to the Adjective Fire Danger Ratings employed by the NFDRS; Low, Medium, High, Very High, Extreme respectively. White areas represent areas of No Data. The areas of no data across the US vary with the changing number and spatial distribution of reporting weather stations for each time point in our study period 2006–13.

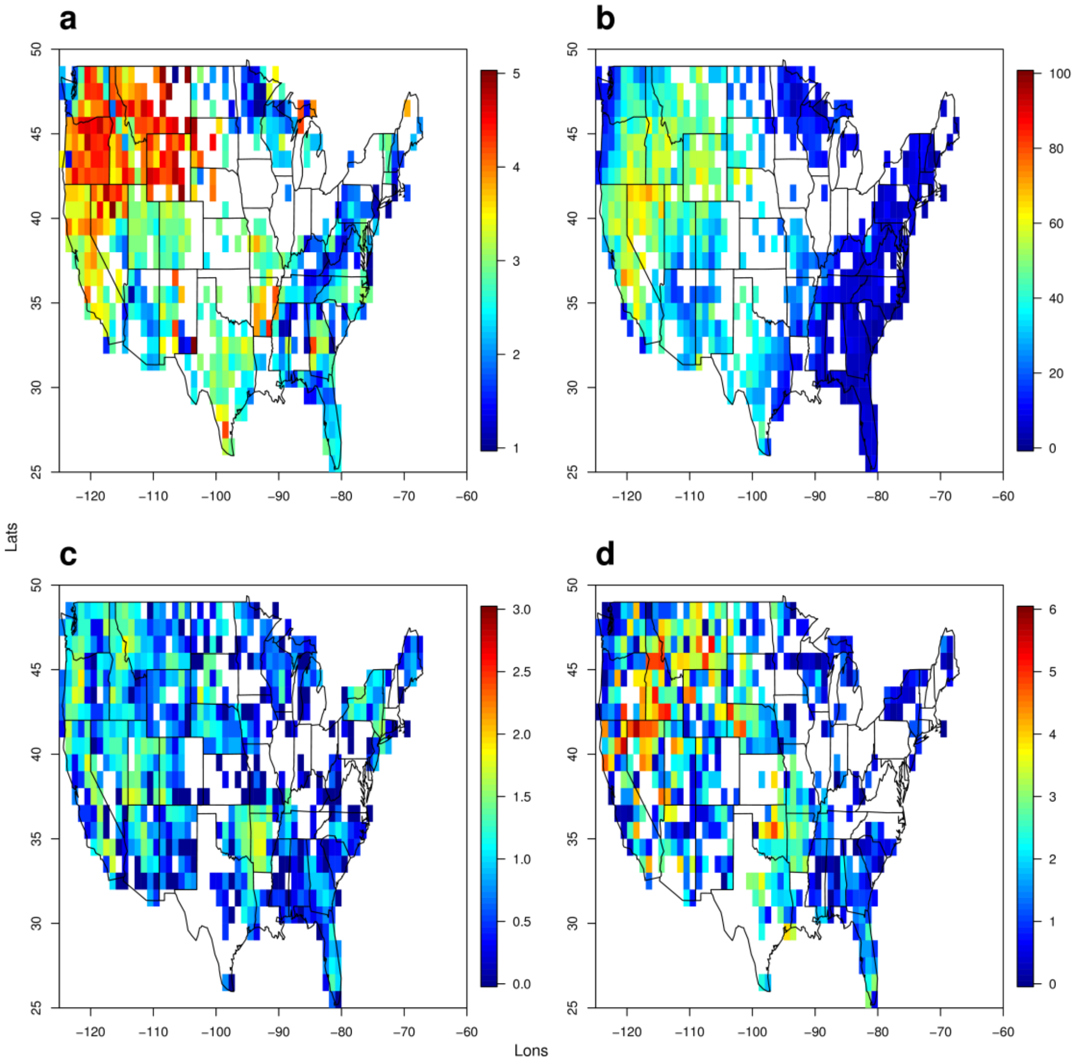

Figure 4.2. Monthly means of (a) Observed Staffing Level (STL), (b) Observed Ignition Component (IC), (c) Fire Occurrence (log10 FO) and (d) Final Fire Size (log10 FFS) for the month of August 2012 on a 1 × 1° degree grid. White areas represent areas of No Data and these are determined by the spatial distribution of reporting Weather Information Management System (WIMS) weather stations for August 2012.

There is always a temporal–spatial resolution-scale trade-off with such assessments. Here I opt for 8 years of daily, and then monthly, fire danger and fire activity data (2006–13) that is summarised at a 1 × 1° spatial resolution (equivalent to 111-km grid square), covering the whole of the conterminous US. Even though the spatial resolution of this study may appear coarse, it has been noted that fire danger indices from the NFDRS are designed to encompass the worst-case burning conditions across large fire danger rating areas, ranging in size from 10^4 to 10^6 ha (Fosberg and Furman, 1971, Freeborn et al. 2015), a scale that is comparable with the spatial resolution used in these analyses, and still informs the majority of US fire management decisions (Freeborn et al. 2015). My overarching aim is to test the relationship between observed fire danger indices (FDIs) and recorded fire activity, in order to assess the ability of the NFDRS to reflect real fire occurrences and large fire sizes, and as such I reconcile fire activity with observed fire danger ratings at the scale over which they are administered.

In order to understand the associations between observed fire danger indices and fire activity, and their spatial variability, this study covers the whole of the conterminous US at a 1 × 1° spatial resolution. I utilise observed daily fire danger data from the NFDRS and recorded fire occurrence and final fire size data from the United States Forestry Service's (USFS) Fire Program Analysis Fire Occurrence Database (FPA FOD) (Short 2015a) for the time period 2006–13.

4.2.1. NFDRS fire danger data

Daily observed NFDRS output data files were accessed and downloaded from the WFAS data archive for the years 2006–13 (WFAS, 2018d). For each day, reporting weather stations are listed with their respective details (e.g. name, latitude-longitude), weather observations, derived secondary outputs, computed fire danger indices and a final Fire danger Adjective Rating. The number and distribution of reporting WIMS weather stations varies daily, with the number of reporting stations ranging from 1500 to 3000. The number of reporting stations varies day-to-day with some weather stations only being operational through some parts of the year (usually peak fire season) and others failing to report owing to human error and malfunctioning stations through the network. Of the fire danger indices listed in Table 4.1, this study considers the Fire Danger Rating (FDR), Staffing Level (STL) and Ignition Component (IC). I focus on these three outputs from the NFDRS because of the heavily managed nature of the environment in the US with regard to fire management policy and the suppression infrastructure deployed annually. I intended to use indices from the final stages of the NFDRS that were directly used in the formation of the final Fire Danger Rating through the fire danger matrix by fire mangers on an operational-daily basis. Other indices that are used in the evaluation of FDIs, such as ERC, SC and BI, were less of a focus for this study because they are not consistently used or selected across the US by fire managers, or even at the same locations or stations because of the constant changes in fire weather and fuel conditions. What is consistent, however, is the use of the STL, which is in turn derived from different combinations of these intermediate indices, along with the IC in the formation of the fire danger rating. The fire danger rating aims to describe the worst current-burning conditions and has five linearly related categories (low, medium, high, very high and extreme). For the purpose of this study, these categories were represented by values 1–5 and will be referred to as the FDR for the remainder of this paper (see Table 4.2 for definitions of each category). The STL can be seen as a required level of 'readiness' based on the fire danger conditions being observed and forecast, and is a way of linking fire danger information to fire-management decisions (Schlobohm and Brain, 2002). Assigned to each STL are predetermined fire-management actions. This index is predictive in nature as it takes current fire danger conditions (represented by either the ERC, BI or SC) and fuel conditions (represented by the selected fuel model) to inform fire mangers on what appropriate actions are necessary given the fire danger conditions. In the fire danger matrix, Staffing levels are described by numeric values 1–5 (with ± or neutral signs), encompassing the five levels of readiness required at the different ends of the fire danger continuum. The IC is defined as the probability that a firebrand will cause a fire that requires suppression action (Schlobohm and Brain, 2002) and is the other constituent index in the formation of the FDR. The IC is calculated from the probability of ignition, which is a function of 1-h fuel moisture, and the probability that a reportable fire will occur, given an ignition, which is a function of the Spread Component (Cohen and Deeming, 1985). The IC is more than just a representation of a probability of ignition, in that it focuses on action and uses the Spread Component (Table 4.1) in its calculation to represent a fire's potential to spread and require mitigative action. Both the STL and the IC are used in the fire danger matrix (Schlobohm and Brain, 2002) to calculate the FDR for a particular weather station and surrounding FDRA. It is because of their integral nature in the formation of the FDR, their representation of the likelihood of ignitions requiring suppression and the level of in-house readiness required, that the present study focusses on the STL and the IC in addition to the FDR to encompass key aspects of fire danger that relate to fire potential and fire activity. Although I do not analyse the ERC, BI and SC directly in this study, they are integral to the calculation of the STL and therefore the FDR, and so their utility is intrinsically considered within that analysed here.

In this analysis I use the reported and published weather station data and their corresponding published observed fire danger indices. By utilising the WIMS weather station-based datasheets from the WFAS website, spatial gaps inherently occur in fire danger data coverage across the US. Therefore, to represent spatial variations and trends in fire danger indices across the conterminous US, the daily FDR, STL and IC data are gridded on a 1 × 1° degree grid using WIMS weather-station location details. Using the published observed FDIs for each WIMS weather station, the mean FDR, STL and IC is calculated when more than one weather station is present in a grid square. I use the published FDIs from each of the WIMS weather stations rather than reproducing FDIs using concurrent weather data because my aim was to capture the knowledge of the fire danger conditions used for each day in the study time period that would have been available at that time. As mentioned previously, each WIMS weather station can have up to four data entries per day using different combinations of the intermediate FDIs and fuel models to form the STL and FDR (National Wildfire Coordinating Group, 2011a); however, the WFAS website only provides access to the first of these entries, where this entry is what is used to construct the fire danger maps that are circulated to the public. As such I have utilised these same data. The daily means of the observed FDIs were then used to calculate monthly means for use in the correlation analysis discussed below.

4.2.2. USFS FPA FOD

Wildfire activity and cause of ignition data was sourced from the USFS's FPA FOD (Short 2015a). This database seeks to amalgamate and standardise US federal, state and local wildfire reports from 1992 to 2013 into one coherent dataset for use in the statistical analysis of wildfire activity. Details of the database's construction can be reviewed in Short (2014). Although the database is incomplete in some aspects, it facilitates high-resolution spatial analysis of wildfire activity across the US (Short, 2015b). From this database, I utilise the discovery date of each recorded wildfire in order to represent newly discovered fire occurrence and its corresponding final fire size (acres) as a measure of fire size and an indication of whether the fire escapes initial attack or is successfully suppressed. I also explore variations in the cause of ignition.

Using the dates of discovery of each recorded wildfire, daily wildfire records of fire occurrence and final fire size were created from 2006 to 2013. With regard to the temporal designation of final fire sizes, I choose to use the discovery date for each fire event from the USFS FPA FOD to represent the final sizes of each fire temporally. Therefore, for each fire I know when it was discovered, and its final size. Each daily record was then applied to the same 1 × 1° grid of the conterminous US as the NFDRS data using the latitude and longitude of each wildfire. Monthly total fire occurrences and monthly total final fire sizes (referred to as FO and FFS respectively) were then plotted and used in the analysis discussed below.

Table A4.1 in Appendix IV provides further details on the data utilised in this chapter with details on how the data was processed and summarised clearly stating the variables created in the process for use in the analysis.

4.2.3. Plotting and correlation analysis

Once these data were collated, observed daily- and monthly-mean FDR, STL and IC maps were created for the years 2006–13 using the longitudes and latitudes for each weather station. The same was undertaken for daily and monthly-total FO and FFS based on the location data for each wildfire record over the same spatial and temporal resolution (Figure 4.2). These maps allow the identification of spatial variations in fire danger index, FO and FFS across the aforementioned time period. Once the data were in this gridded format, Spearman Ranked correlations (at a significance of $p \leq 0.05$) were conducted for each grid square across the conterminous US using the observed monthly-means (FDR, STL, IC) and monthly-totals (FO, FFS). Each of the three fire danger indices were correlated with FO and FFS, creating six correlation pairs. Spearman Rank correlation was chosen as it allows both ordinal and continuous data to be correlated. Once again, it should be stressed that for FFS the date being used is that of each fire's discovery. Therefore for each fire, I know when it occurred and what its final fire size was, and I correlate both of these with the observed fire danger conditions (represented by the FDR, STL and IC) on the day each fire was discovered. Six maps of correlation coefficients were produced (with a significance of $p \leq 0.05$, non-significant correlations are indicated by grey pixels) in order to see the distribution of coefficient strength across the US between each respective Fire Danger Index and fire activity metric pair (Figure 4.3). It should be noted that correlations were calculated in grid squares where reporting NFDRS weather stations were present, with fires present or not-present, and not only for those locations where fires occurred. This means the spatial distributions of correlation coefficients seen in Figure 4.3, and the resulting ‘gaps’, are a representation of the distribution of reporting weather stations, not the locations of wildfires within a grid square. To support the interpretation of the maps produced in Figure 4.3, histograms of correlation coefficients were produced (Figure 4.4). These highlight the frequency of the different strength of correlations between each observed FDI and fire activity metric in order to highlight which FDIs correlate most with FO and FFS. I have spatially explored the strength of the correspondence between ignition cause and FO and FFS for the three most common causes of ignition of fires in the FPA FOD to highlight any variations in fire cause spatially across the conterminous US (Figure 4.5).

To further understand the nature of the observed fire danger data, histograms showing the frequency of fire occurrences along each of the selected fire danger index’s range of possible values were produced (Figure 4.6). To complement the correlation maps presented in Figure 4.3, corresponding scatter plots for each correlation pair were also produced in order to explore the distribution of each fire danger index with FO and FFS (Figure 4.7). These scatter plots take the observed monthly-mean FDR, STL, IC values and monthly-total FO and FFSs for each month from 2006 through 2013 for the whole of the US. Percentile analysis of FO and FFS data across the three FDIs’ respective value ranges was also conducted in order to highlight trends in fire activity across the spectrums of FDR, STL and IC (Figure 4.7). The moving-mean for monthly-total FO and monthly-total FFS (±1 s.e.) was also calculated to further identify trends in FO and FFS with respect to each individual FDI (Figure 4.8).

Table A4.2 in Appendix IV provides further details on the different steps of the analysis in this chapter with explicit descriptions of the variables used, with details on the statistical techniques used, their definition, their justifications for use, and information on how to interpret the specific outputs from each step of the analysis.

4.3. Results

From the data and processing methods described above, monthly-means of the three observed fire danger indices and monthly-totals of the two metrics of fire activity were produced for each grid square from 2006 through 2013 and these 96 time points were used to produce Spearman Rank correlation coefficient maps ($p \leq 0.05$) and national scatter plots.

4.3.1. Correlation coefficient maps and histograms

Figure 4.3 shows the spatial distribution of correlation coefficients across the conterminous US for each of the six correlation pairs. Grid squares with insignificant coefficient scores ($p \leq 0.05$) are shaded grey, whereas grid squares where no NFDRS weather station data are reported are white. Across the six plots it can be seen that there are a range of coefficient values, ranging from strong correlation coefficients in Washington, Oregon, northern California, Idaho, Montana and Nevada and a mix of relatively strong and weaker coefficients (ranging from 0 to 0.25) in the Southern and Eastern Geographic Area Coordination Centres (GACCs) of the US.

Figure 4.3a–c shows the variation in coefficient strength of each observed fire danger index (FDR, STL, IC) when correlated with FO. From looking at the distribution of coefficient scores across Figure 4.3a–c, persistent areas of strong positive correlations appear to be in Oregon, northern California, and parts of Idaho and Montana for all of the fire danger indices. The rest of the country, however, shows a patchwork mixture of correlation strengths between the three observed FDIs and FO. Out of the 3 observed FDIs examined, there appear to be more IC grid squares that have strong positive correlations with FO, with areas of high correlation being most notably in the Northwest, Northern Rockies, Great Basin and Northern California GACCs. Figure 4.3d–f shows the variation in coefficient strength of each observed fire danger index (FDR, STL, IC) when correlated with FFS. The patterns of correlation strength between the FDIs and FFS appear to strongly mirror the associations displayed between the FDIs and FO with similar regions displaying strong positive correlations. IC appears to correlate most strongly with the FFS when compared with STL and FDR, most notably in the Northwest, Northern Rockies, Great Basin and Northern California GACCs. This is evidenced both in Figures 4.3 and Figure 4.4 through the number of grid squares with correlation coefficients being greater than 0.5 (Figure 4.4) and the spatial distribution of these coefficients in the aforementioned regions of the US (highlighted as orange and yellow grid squares, Figure 4.3).

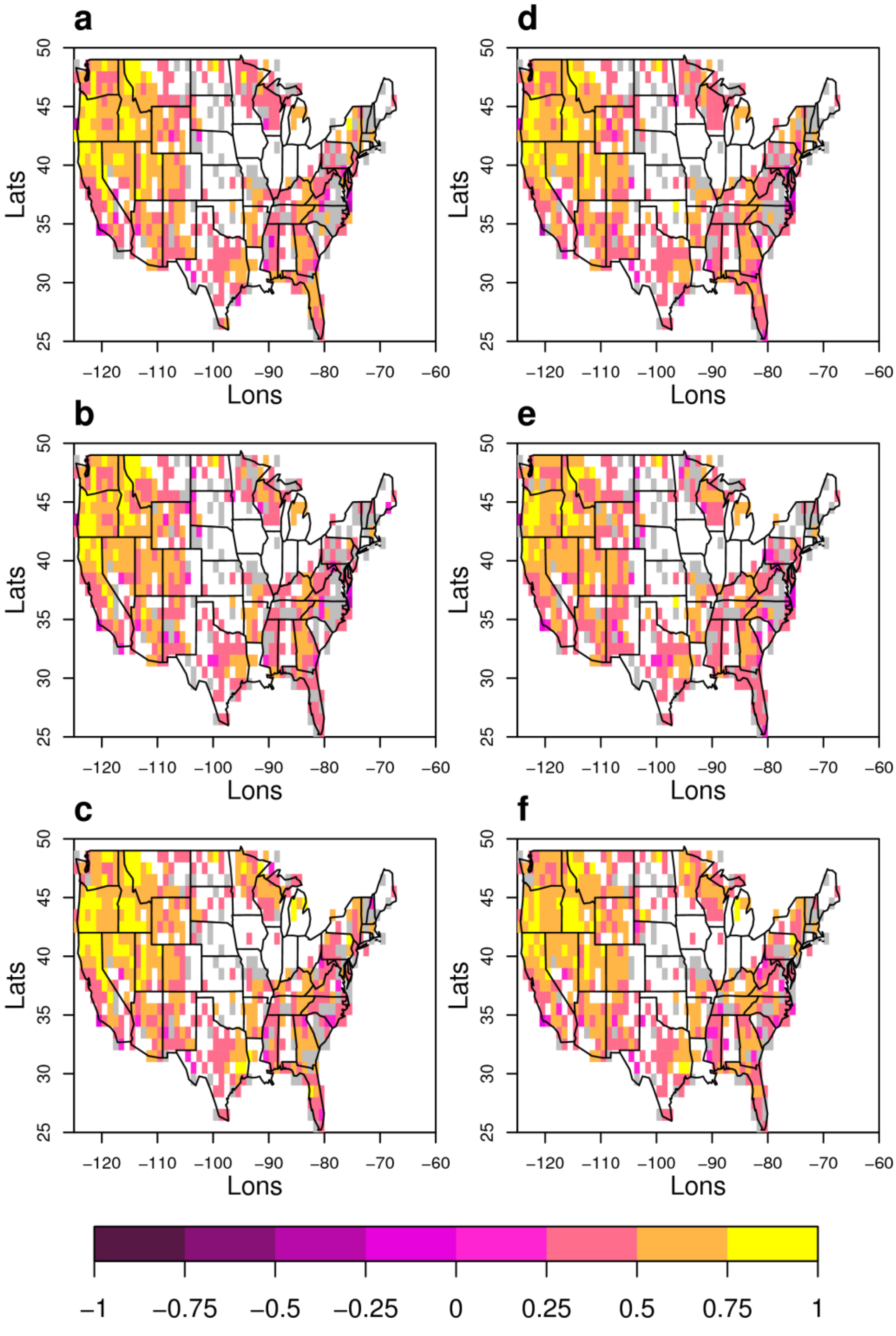

Figure 4.3. Correlation coefficients (Spearman Rank Correlation) of 1 × 1° degree gridded l data for monthly total Fire Occurrence (FO) v. observed (a) monthly mean Fire Danger Rating (FDR), (b) monthly mean Staffing Level (STL), (c) monthly mean Ignition Component (IC); and monthly total Final Fire Size (FFS) v. observed (d) monthly mean FDR, (e) monthly mean STL, (f) monthly mean IC. Grey areas represent non-significant correlations (p ≤ 0.05) and white areas represent areas of No Data. The spatial distribution of areas of no data is determined by the absence of reporting weather stations across our study's time period with no correlation being calculated for these areas.

To complement the six plots in Figure 4.3, corresponding histograms of the correlation coefficients can be seen in Figure 4.4. This identifies what magnitude of correlation strength (positive or negative) most frequently occurs across the US and further exhibit different relationships between the observed FDIs and FO/FFS. Across the six plots (Figure 4.4a–f), it can be seen that most of correlations between the observed FDI and FO/FFS are positive. However, the frequency and magnitude of these positive correlations appear to vary between the six correlation pairs. The distribution of correlation strengths appear to be broadly consistent when comparing the observed FDIs with each metric of fire activity. In other words, the distribution of correlation coefficients between FDR-FO and FDR-FFS appear broadly similar. With the same being apparent for the IC and STL. What is striking, however, is that the majority of correlation coefficients between STL-FO, and STL-FFS are weaker positive correlations with the majority of scores ranging from 0.25 to 0.5, whereas the opposite is true for the respective FDR and IC correlation coefficients, where the majority of correlations have scores ranging from 0.5 to 0.75. This would indicate that the FDR and IC correlate more strongly with the fire activity metric than the STL across the conterminous US.

When comparing all plots in Figures 4.3 and 4.4 it is apparent that overall there are strong correlations between each of the observed fire danger indices (FDR, STL and IC) and the fire activity metrics (FO and FFS) for much of the US. However, there are apparent differences in correlation strength for certain regions of the country, and there are a larger number of strong-positive correlations between FO/FFS and the FDR and the IC than there are with the STL.

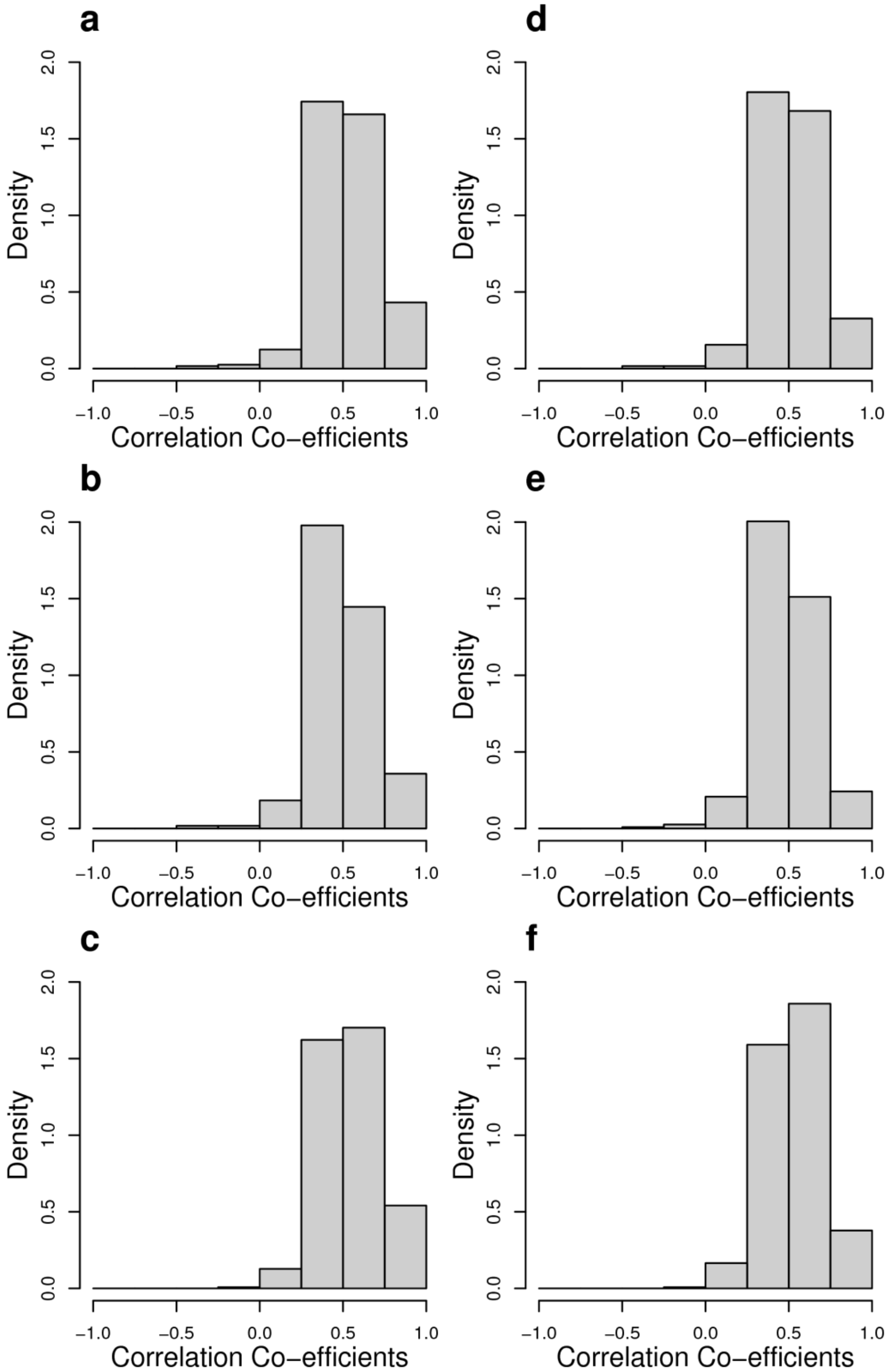

Figure 4.4. Histograms of correlation coefficients (Spearman Rank Correlations) for the corresponding maps plotted in Figure 4.3, which show monthly total Fire Occurrence (FO) correlated with observed (a) monthly mean Fire Danger Rating (FDR), (b) monthly mean Staffing Level (STL), (c) monthly mean Ignition Component (IC); and monthly total Final Fire Size (FFS) correlated with (d) monthly mean FDR, (e) monthly mean STL, (f) monthly mean IC.

Figure 4.5 reveals that there are distinctive spatial patterns in fire cause. Lightning caused fires are more common in states in the Northwest, Northern California, Great Basin and Southwest GACCs as well as in Florida, where they also lead to larger FFSs (Figure 4.5a, d). Debris-burning-caused fires seem to occur almost exclusively in the Southern GACC but do not lead to the largest fire sizes in this dataset. They do, however, appear to relate to the largest FFS in the areas of high debris-burning-caused FO. Arson-caused fires also appear to occur most in the Southern GACC as well as in New York State, again these do not generate fires as large as those in the West but they do contribute to large final fire sizes in the region (Figure 4.5c, f).

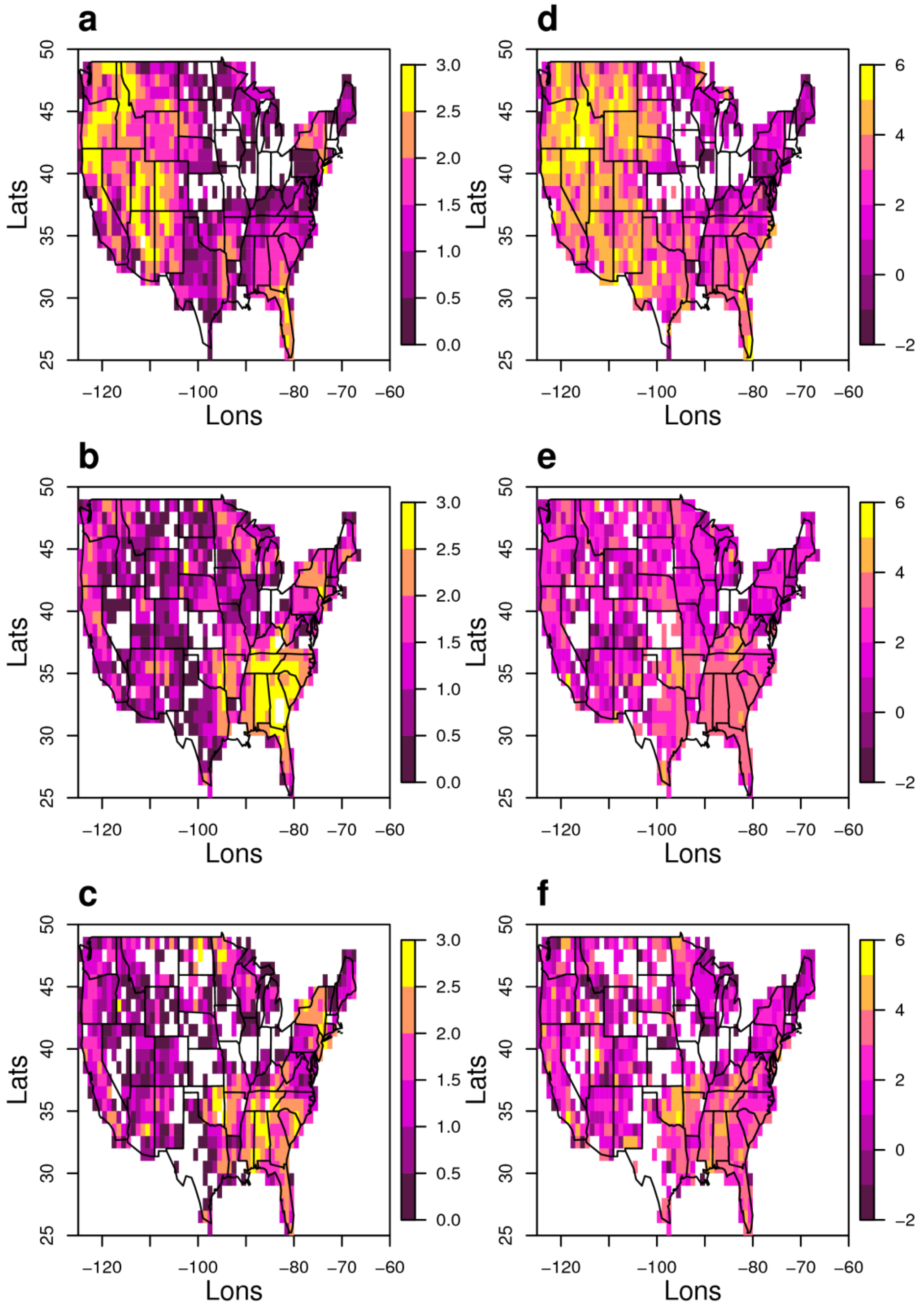

Figure 4.5. Maps of monthly total FO (log10) and monthly total Final Fire Size (FFS) (log10) for the three most common fire causes in the FPA FOD from 2006 to 2013; Lightning (a, d), Debris Burning (b, e) and Arson (c, f), (FO, FFS respectively).

4.3.2. National scatter plots and summary trends

The histograms in Figure 4.6 show the frequency of fire occurrences across the three selected observed fire danger indices' ranges as well as highlighting the mean and median values (blue and red dashed lines respectively). Across all three histograms it can be seen that high-index values are rare occurrences, whereas for FDR and STL (Figure 4.6a, b) values of 1 are the most prevalent. The distribution of observed FDR values (Figure 4.6a) exhibit a left skew with a mean value of 1.88 to and a median values of 1.76. The distribution of observed STL values in Figure 4.6b shows a less distinguishable skew to the left with the mean and median values at 2.44 and 2.43 respectively, but a slight right-hand tail can still be made out upward from observed STL values of 3. The distribution of observed IC values (Figure 4.6c) displays evidence for a truncated normal distribution centred on an observed IC value of ~10. The distribution, however, has a strong right sided skew (mean and median values of 19.76 and 15.18 respectively) with a long right-hand tail towards extreme values.

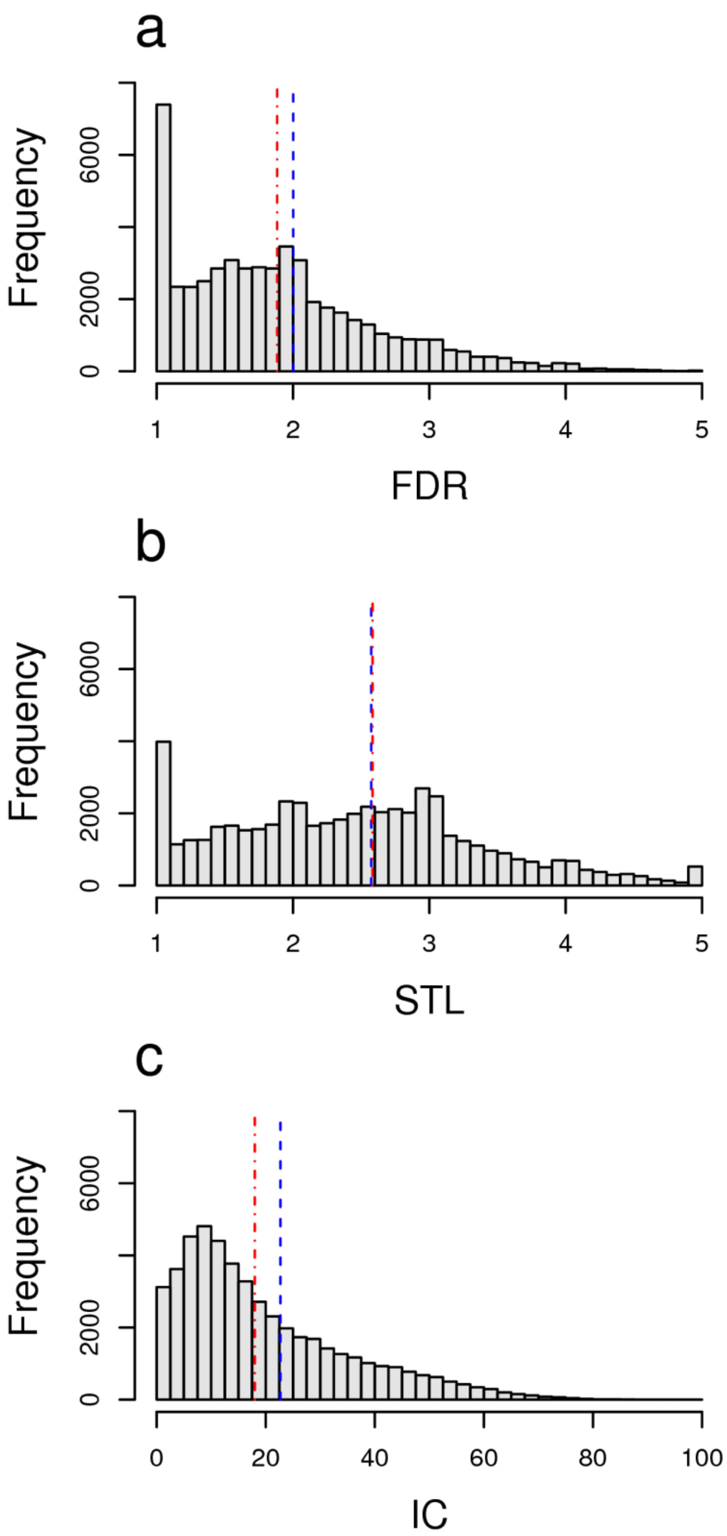

Figure 4.6. Histograms of observed monthly mean (a) Fire Danger Rating (FDR), (b) Staffing Level (STL) and (c) Ignition Component (IC) data. Vertical lines indicate mean (blue, dashed) and median (red, dot-dashed) values for each of the monthly summarised observed Fire Danger Indices datasets.

When considering all grid squares together in aggregate to represent the whole of the conterminous US, the scatter plots seen in Figure 4.7 show striking patterns pertaining to extreme values in the fire activity metrics; monthly total FO and monthly total FFS, relative to the values of the corresponding observed FDI; monthly mean FDR, STL and IC, as well as percentile trends ranging from the median to the 99th percentile. The black lines represent the median value of FO/FFS at the respective position in each of the observed FDI spectrums (blue lines indicate the 75th percentile value, green lines indicate the 95th percentile value, and red lines indicate the 99th percentile value). When considering the scatter-points, in Figure 4.7a, d, extreme values of FO and FFS at low and mid observed FDR values can be seen, respectively. This pattern is also clear in Figure 4.7c, f, where the highest values for FO occur at observed IC values of ~20, with largest FFS at observed IC values of 50. The distribution of fire occurrences across the observed STL spectrum seen in Figure 4.7b shows a less pronounced mid-range peak in FO whereas the upper-range of values appear to have a greater number of very large FFS. When considering the percentile trend-lines it can be seen that across all subplots in Figure 4.7 both the median and 75th percentile are rather flat across all respective observed FDR, STL and IC values. Most variations in the trend can be seen at the 95th and 99th percentile with each FFS plot (Figure 4.7d–f) exhibiting increasing FFS towards the upper end of each fire danger index's values. A similar upward trend in FO with respect to observed STL value (Figure 4.7b) can be seen; however, higher values in FO are present at low and low-mid values of observed IC and FDR, respectively. It should be noted that the apparent 'flatness' of the median and 75th percentile is due to high frequency of 0 values in the fire activity datasets. Measures of 0 values in the FO and FFS data are still valid data entries, because a high observed FDR can still result in no fire occurring. What is of interest though, in light of the high frequency of zero values, is the range of potential FO and FFS values at the respective mid and mid–low observed FDI values. The extreme-values ranges are consistent across all of the observed FDI and fire activity metric pairings presented in Figure 4.7. For FO, the greatest range in potential values occur at mid–low index values, whereas for FFS they occur at the intermediate and high index values.

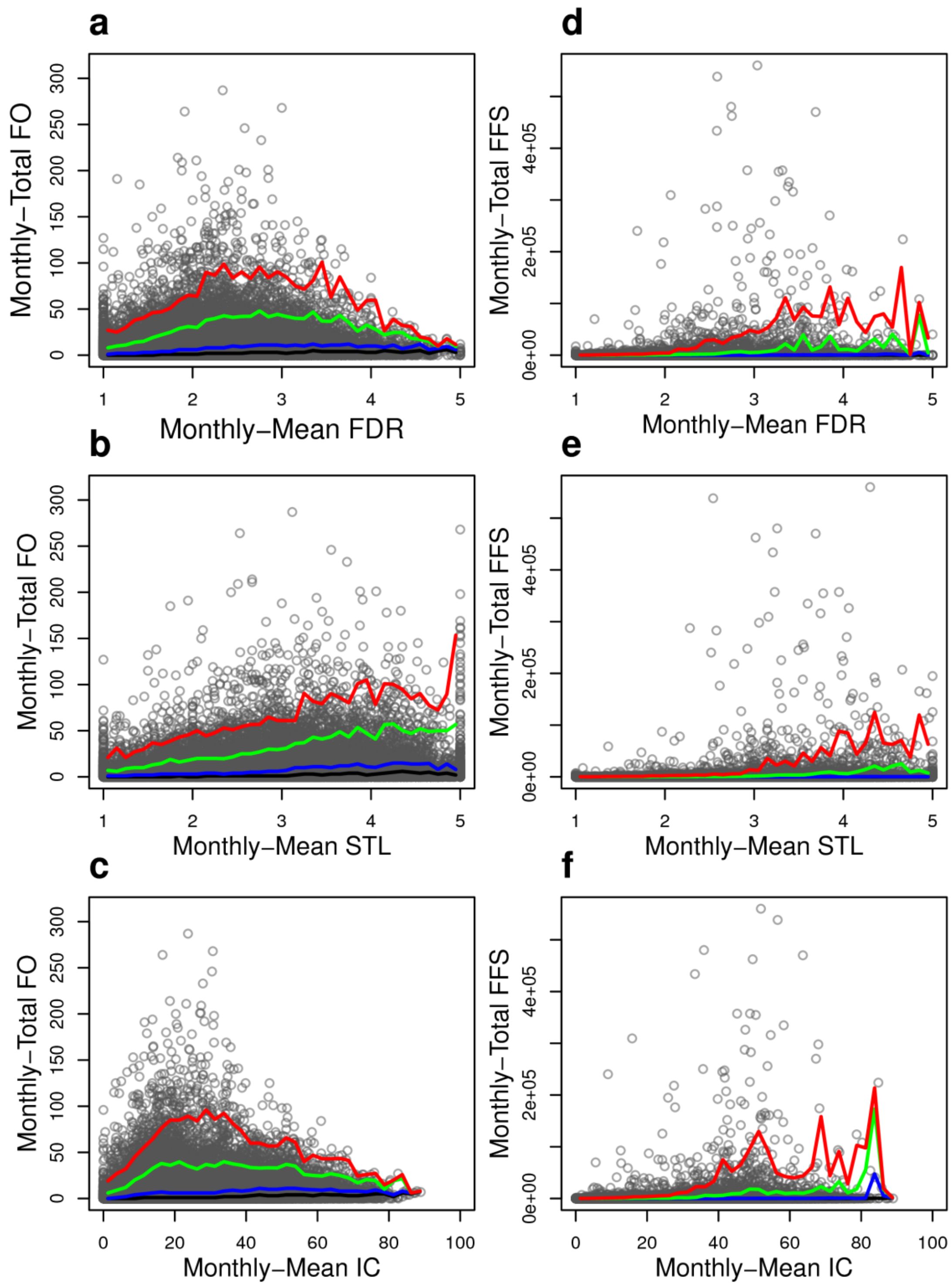

Figure 4.7. Scatter plots of gridded monthly total Fire Occurrence (FO) v. observed (a) monthly mean Fire Danger Rating (FDR), (b) monthly mean Staffing Level (STL) and (c) monthly mean Ignition Component (IC), and monthly total Final Fire Size (FFS) v. observed (d) monthly mean FDR, (e) monthly mean STL and (f) monthly mean IC, for all grid squares. Lines represent percentiles of monthly total FO and monthly total FFS distributions plotted against FDR, STL and IC (black, median; blue, 75th percentile; green, 95th percentile; red, 99th percentile).

Figure 4.8 shows the moving-mean of monthly total FO, monthly total FFS, and log10 monthly total FFS (±1 s.e., dashed lines) after being normalised by frequency (Figure 4.8a–c respectively) along each observed Fire Danger index spectrum, FDR, STL and IC. In Figure 4.8, the solid black lines represent the observed FDR, red lines represent the observed STL and blue lines represent the observed IC moving mean, with corresponding dashed lines representing the standard error window. For FO, peaks can be seen at intermediate values of observed FDR, with more fires being present at these values than at high observed FDR values, mirroring trends indicated in Figure 4.7a. A consistent upward trend in FO can be seen along the observed STL spectrum with more fires occurring on days with higher observed STL values. For the observed IC, however, there is less of a trend displayed against FO, the number of fires appears to plateau at low–intermediate levels of observed IC and doesn't drop off substantially towards the upper end of its value range. Additionally, positive upward trends can be seen in FFS (log10) along each of the observed FDIs, with fire sizes plateauing at 404.69–4046.86 ha (1000–10 000 acres) at mid-FDI values. The FFS does exhibit some further peaks at the upper ends of the IC and STL value ranges; however, as indicated by the wide standard error windows, these high-value peaks in FFS appear to be artefacts of under sampling for the corresponding observed IC values with a small number of extremely high FFS fires being present and skewing the moving mean.

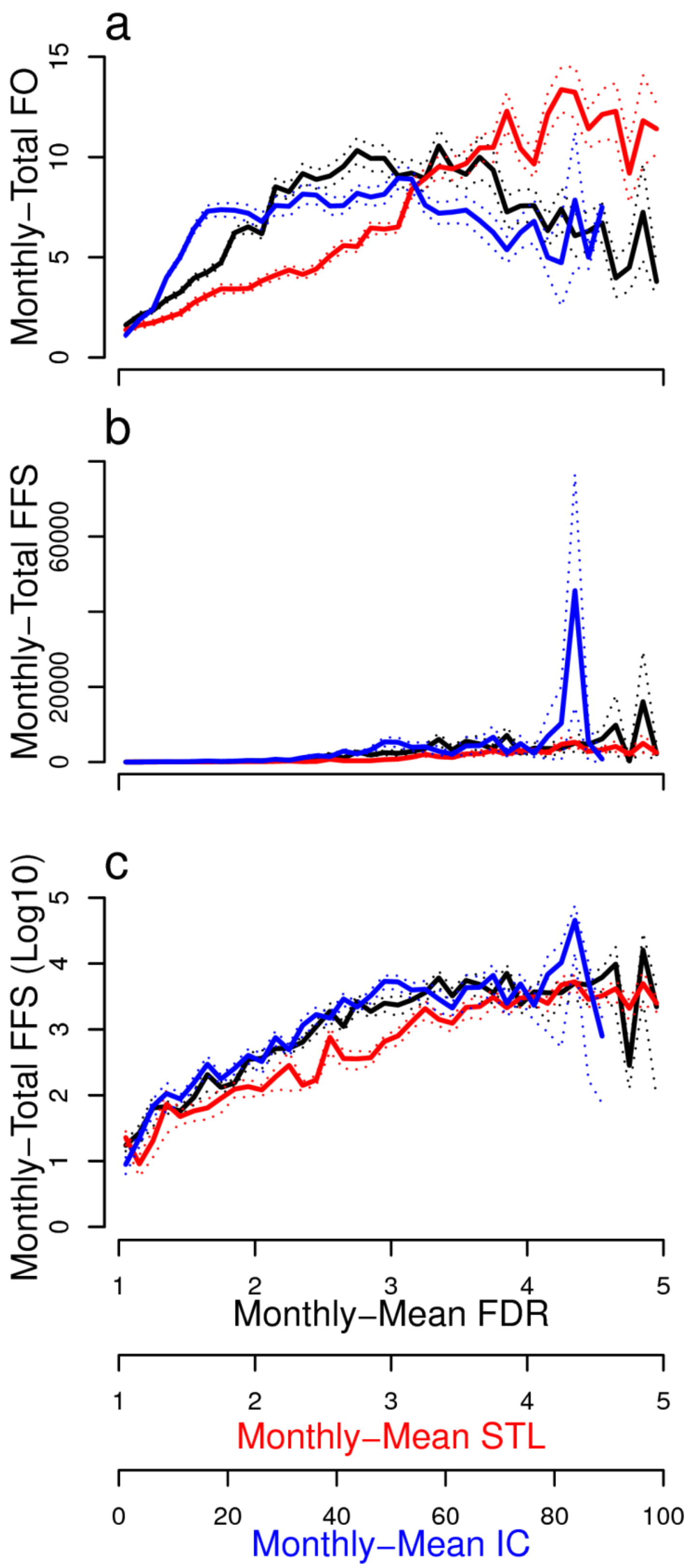

Figure 4.8. Plots of the moving-mean (solid line) ±1 s.e. (dashed lines) for (a) monthly total FO, (b) monthly total Final Fire Size (FFS) and (c) monthly total FFS (log10), along each observed Fire Danger Index; Fire Danger Rating (FDR) (black), Staffing Level (STL) (red) and Ignition Component (IC) (blue).

4.4. Discussion

This analysis reveals that the strength of correlations between each pair of observed FDI and fire activity metrics are not consistent across the country. Areas in the Eastern and Southern GACCs exhibit weaker or more mixed correlations than in the areas of the Northwest, Great Basin, Northern California and the Northern Rockies GACCs where stronger positive correlations are exhibited (Figure 4.3). Moreover, the strength of correlations varies between the observed FDIs and each fire activity metric, with the observed IC and observed FDR exhibiting the most strong-positive correlations, and the observed STL displaying weaker positive correlations (Figure 4.4). This spatial pattern (Figure 4.3c) is consistent with the correlation between climatically derived seasonal IC forecast validation data and fire counts produced by Roads et al. (2010). Although the magnitude of correlation strength may differ between this current study and that of Roads et al. (2010), the regions of highest correlation between FO and IC seem to correspond between the two studies, namely in northern California, Oregon, northern Idaho, western Montana, Utah and Colorado, as well as areas of low correlation, namely southern California and south-west New Mexico. The similarities and differences between these studies appear to relate to the underlying data explored; here I have utilised the observed FDI data as calculated directly from the WIMS weather stations used by the NFDRS, whereas the FDIs presented in Roads et al. (2010) are validation forecasts calculated using seasonal climate model forecasts from regional and global spectral models. However, because of the restricted spatial extent of the fire count database used (Western US only), Roads et al. (2010) are limited in the extent across which they could explore correlations between FDIs and fire counts.

In the current analysis, there may also be underlying reasons why the observed NFDRS fire danger outputs could perform better in some areas than others. It is likely that region-specific vegetation–climate interactions require additional updates. For example, past incarnations of the NFDRS, and subsequent versions, have made improvements in regard to drought in typically humid environments, as well as overrating fire danger in some locations during autumn, or following rainfall events (Burgan, 1988). These revisions that were made in 1988 were focussed on improving outputs for the east and southeast of the US (Hardy and Hardy 2007). Therefore, similar regional inconsistencies may suggest other climate–vegetation–fire interactions remain poorly represented in some regions in the current version of the NFDRS fuel models or fire danger calculations. Each different observed FDI in this study describes a different aspect of fire potential, i.e. the probability that a firebrand will propagate a fire requiring suppression (IC), the level of readiness required (STL) or the overall burning conditions (FDR). Regional differences in climate, fuel type or fire management policy all play important roles in the nuances of each FDI (ERC, IC, BI, SC) calculation and alter the derived FDR and STL's correspondence to actual fire activity.

It may also be that significant variations between the length and timing of the fire season may influence either management decisions or interact with the application of the FDIs. In this US scale analysis it was not possible to reflect variations in the length of the fire season between regions. Therefore regionally focussed work might look to run a similar analysis for individual variations in fire season for different GACCs in the future and this may become an important consideration in future iterations of the NFDRS. The ignition sources of fires appears to also vary considerably between GACCs (Figure 4.5). The majority of fire occurrences in parts of the Western US (Northwest, Northern California, Great Basin and Southwest GACCs) appear to be more dominated by natural causes of ignition, e.g. lightning (Figure 4.5a), whereas in the Southern GACC debris burning and arson appear to be linked to the highest fire occurrences (Figure 4.5b, c). Lightning ignited fires in the Northwest, Northern Rockies, Great Basin and Northern California GACCs lead to larger final fire sizes than those ignited by debris burning of arson in the Southern GACC (Figure 4.5d–f) and therefore might require higher STLs. This is interesting because there is a weaker correspondence between observed STL and large final fires sizes in the Southern GACC (Figure 4.3e). It may be that public perceptions of fire danger in the Southern GACC are different from those in other GACCs. Perhaps the consequences of human ignition in the Southern GACC is less well understood by the local community or that human actions are far less simple to account for in land-management strategies. Additionally, it should be noted that FDR and STL both utilise local fire manager knowledge in their calculation, which introduces human subjectivity that can affect outputs and is difficult to capture in such analyses.

The implications of the apparent geographical inconsistencies in correlation strength between the observed FDIs and the metrics of fire activity (Figure 4.3), could be substantial if considering utilisation of NFDRS outputs to model future fire danger across the US because of the apparent lack of portability of the indices across diverse ecoregions and fire systems, which would be anticipated to change in the future owing to biogeographic shifts in ecosystems and land use changes in response to climate change. It would appear that additional studies might seek to improve the current application of the NFDRS in the Eastern and Southern GACCs of the US and raise public awareness of their actions. As such, these should be seen as areas of focus for any future developments of the NFDRS.

Considering the US as a whole, I find that mid–low values of observed FDR result in extremes in FO and a steadily increasing trend in FFS. The patterns evident in Figure 4.7a, d are contrary to the expectation that as observed fire danger increases, the number and sizes of fires would increase monotonically and so low–mid range observed FDR values seem to misrepresent assumed fire activity here. One reason for this may involve the response to the observed FDR by either the public or fire managers, e.g. if necessary prevention actions are not undertaken. Alternatively fire managers may not intend to suppress fires during low danger ratings, and perhaps allow them to burn naturally in low risk conditions, according to ecosystem management practices adopted subsequent to the total fire suppression policy used up until the 1970s (van Wagtendonk, 2007). Such an approach would accord with observed high FO arising without high FFS.

Similar relationships can be seen in Figure 4.7c, f with extremes in FO and FFS appearing out of sync across the observed IC spectrum. At the low end of the observed IC spectrum, these high occurrences of fire appear to be those that either didn’t require suppression or were suppressed successfully, hence the low FFSs. Such conclusions can be drawn as the IC is defined as the probability that, given an ignition source, a fire will propagate and require suppression (Schlobohm and Brain, 2002). The IC is therefore not only a measure of FO through the probability of ignition, but a measure of FOs that will potentially result in large fires (large FFS) unless acted upon. Therefore the fact that the low observed IC values correspond with high FO and low FFS indicates that the fires occurring may not have required suppression, otherwise their corresponding observed IC values would have been higher, hence the largest FFS can be seen at the higher end of the observed IC scale. This would indicate then that the IC appears to capture differing levels and types of fire activity well in that peaks in FFS only occur at higher observed IC levels. This relationship may be reflective of changes to management practices that allow low fire danger fires to burn and remove dead fuel load build up in order to prevent re-occurrence of large ecologically destructives fires such as those in Yellowstone in 1988 (van Wagtendonk, 2007).

To complement a discussion of the success of the observed IC in capturing different characteristics of fire activity, the relationships between observed STL values, fire occurrences and their final sizes brings an additional perspective. Within the scope of this study, the observed STL-FO and observed STL-FFS relationships allude to the levels of readiness needed to deal with the workforce pressures associated with wildland fires if they were to be ignited on a particular day based on the fire danger indices calculated to represent the day’s conditions. This would imply that as observed STL values increase, either the number of fires or their sizes should increase as the levels of readiness are required to be higher. From Figure 4.7b, e, it can be seen that there are both upward trends in FO and particularly FFS along the observed STL spectrum. There is no distinguishable peak in extreme FO values across the observed STL spectrum, especially when compared with patterns exhibited by the other selected FDI used in this study. Instead an upward trend in FO can be seen across the observed STL spectrum. Moreover, there is a notable number of instances of extreme values of FFS at the upper end of the observed STL spectrum. This implies that staffing resources are suggested to be most needed in conditions when fires may lead to the large fire sizes indicating that the observed STL appears to be well linked to preventing major fire spread rather than just the occurrences of fire. The observation that extreme FFS relates to the greatest observed STLs may also indicate that sufficient staffing levels cannot be met using existing fire management resources, and may point to extension of resources being required in the future.

Figure 4.8 complements the trends discussed above, and, when considered with Figure 4.7, indicates that FFS has a positive relationship with each FDI whereas FO instead shows a non-monotonical relationship with observed FDR and observed IC, and a positive relationship with observed STL. This implies that the fire danger indices provide an effective signal for ‘dangerous’ fires (i.e. those that might spread out of control leading to large FFS). I speculate that the non-monotonical relationship in FO v. observed FDR and observed IC may be due to fires being allowed to remain unsuppressed at perceived ‘lower’ risk levels (e.g. as part of the fire manager’s strategy) and the FDR’s aim is to facilitate prevention or containment of major out-of-control fires that ultimately lead to the greater FFSs. This is further supported by the histograms presented in Figure 4.6, where most incidences of fires occur at low observed FDI levels implying that these are perceived as ‘non-dangerous’ and are acceptable (possibly a reflection on the policy shift from total fire suppression to prescribed burning).

I believe that the implications of the findings of this study could be of use to both fire administrators as well as the wider fire science community. By revealing spatial inconsistencies in the relationship between the NFDRS’s observed FDIs and metrics of fire activity (FO and FFS) I highlight important ramifications for the utilisation of FDIs in some regions both for the present day and forward modelling of future aspects of fire danger across the US based on climatic and vegetation variables. For example, the regional inconsistencies that have weaker correlation coefficients (e.g. the Southern and Eastern GACCs of the US and the fuel groups they represent) would require more consideration if their current FDIs were to be applied to consider potential changes to fire danger in the future. More critically, these regions may require additional focus when developing future improvements of the NFDRS, particularly in the Southern GACC. It should be noted, however, that overall, the results I present here indicate that the models implemented within the NFDRS are well founded and the observed FDIs analysed here appear to well capture the different aspects of wildland fire activity experienced across the US.

4.5. Conclusion

I have been able to indicate that the intrinsic processes within which the FDIs of the NFDRS are well founded. However, discrepancies remain in terms of the performance of the NFDRS between different regions of the US, e.g. compare the North and West with the South and East. In particular I highlight that further development of the application of the NFDRS is required in the Southern and Eastern GACCs. I reveal that there appear to be complex interactions between metrics of fire activity and the observed FDIs explored here. Interestingly I have shown that high occurrences of fire are more common at mid–low observed FDRs and low observed ICs, and may align with perceived shifts in management practices currently employed across the US. Although in general, large final size of fires appears to correspond well to high observed STL, indicating that the ability of the NFDRS to apportion the resources required (STL) to combat large fires is well developed. However, it should be noted that even with high observed STLs, large final fire sizes do occur, suggesting that new resource allocations might be appropriate in order to deal with noted rises in large wildfire events over recent years (Dennison et al. 2014).

As yet, how the NFDRS's FDIs function in a forecast setting and as a tool for management strategies remains untested against fire activity data. Future research might seek to explore the effectiveness of the NFDRS and its utility by fire administrations by building an understanding of the forecasting accuracy of the NFDRS FDI and their resulting effect on the recorded fire activity. Such exercises would be able to build on this study and test whether the accuracy of predictions result in either the reduction of fire occurrence or prevent larger final fires sizes. This would allow tests of whether management responses to forecast FDIs are able to initiate mitigative actions successfully.

“The Corridor of [Un]certainty”

Geoffrey Boycott

Chapter 5: How accurate are the NFDRS 1-day forecasts?

5.1. Introduction

Following on from Chapter 4 (Walding et al. 2018), this chapter applies the same data processing techniques with a new set of analyses to explore how accurate the 1-day forecasts of fire danger indices from the NFDRS are in comparison to the respective observed fire danger conditions across the conterminous US for the period 2006-2013. This chapter then explores the relationships between forecasted fire danger indices and metrics of fire activity; the occurrence of fires, and fire final size (acres) and contrasts these relationships with those presented in Chapter 4 that focus on the relationships between observed fire danger indices and wildfire activity at the monthly timescale.

There is a need for accurate forecasting of fire danger conditions to ensure that appropriate and effective suppression action can be undertaken safely, efficiently, and successfully (Scott et al. 2014). 'Over-estimating fire behaviour can be easily adjusted without serious consequences, but underestimates of fire behaviour [and therefore fire danger] can be disastrous' (Rothermel, 1980, Scott et al. 2014). Depending on the timeframe and nature of management actions and the operational utilization of fire danger forecasts, inaccurate forecasting and especially the under-forecasting of fire danger could have a number of ramifications across a range of timescales across different regions of the conterminous US (Table 5.1, Rothermel, 1980, Scott et al. 2014).

Table 5.1. The scope of quantitative wildland fire behaviour prediction (Adapted from Scott et al. 2014 and Rothermel, 1980).

Fire Situation	**Intended Use**	**Resolution**		**Relative usefulness**	**Ease of prediction accuracy**	**Impact of inaccurate prediction**
		Timeframe	**Area**			
Possible	Training	Long-term	N/A	Moderate	Extremely to very easy	Minor or minimal
	Long-range planning (e.g. preparedness system development)	Yearly/ seasonal	State/ province/ territory	Good	Easy to moderately easy	Significant
Potential	Short-term planning (e.g. preparedness system development)	Daily/ weekly	Forest/ district	Very Good	Moderately difficult to difficult	Serious
Actual	Near real-time (e.g. automated dispatch, project fires escaped fire situation analysis)	Minutes to hours	Stand or site-specific	Excellent	Very to extremely difficult	Critical

For instance the public perception of fire danger warning systems could alter if persistent over-forecasting of fire danger occurs in specific locations. This would reduce the effectiveness of messages delivered through Smokey Bear and state/local fire outlets owing to the 'false alarm effect', defined as the 'credibility loss [of an early warning system] due to a false alarm' (Breznitz, 1984). Although human responses to natural hazards are complex, and the effect of false alarms is still debated in the wider context of news coverage and the potential benefits to raising hazard awareness (Barnes et al. 2007), the cry-wolf effect is still often a widespread source of speculation and concern within the warning community (Dow and Cutter, 1998).

Moreover the inaccurate forecasting fire danger conditions may have other consequences. For instance, fuel management operation opportunities may be missed at critical fire weather windows outside of the fire season, or worse, during active suppression actions, firefighters could be placed under unforeseen severe risks.

The US Forest Service (USFS) National Fire Danger Rating System (NFDRS) currently deploys 1-day forecasts of fire danger through the Wildland Fire Assessment System (WFAS), and other more regional and state-focussed outlets such as the National Geographic Area Coordination Centers website (https://gacc.nifc.gov/index.php, accessed 19/2/18) and the Texas Weather Connection (http://twc.tamu.edu/tfd, accessed 19/2/18). The aim of these forecasts is to predict the potential for dangerous fire activity in order to facilitate fire suppression efforts by fire administrations (Schlobohm and Brain 2002). These forecasts are used by fire managers to facilitate informed decisions on active fire suppression activities, fuel management strategies and resource allocations, as well as convey fire danger information to the public.

Daily NDFRS products are produced following a sequence of procedures. Fire weather observations are recorded once per day at ~1pm Local Standard Time (LST) at each of the reporting weather stations in the Fire Weather Network. Weather observations are recorded and reported to the Weather Information Management System (WIMS) and these are utilised with local site descriptors defined by fire managers to calculate fuel moistures and fire danger indices for each reporting fire weather station. To calculate 1-day NFDRS forecasts, forecasters from the National Weather Service (NWS) use the observed local weather observations for each of the reporting weather stations in WIMS to issue trend forecasts for fire weather forecasts for either the specific reporting weather station or fire weather zones (defined as a group of fire weather stations that experience the same weather change or trend, (Schlobohm and Brain, 2002)). These forecasts of fire weather are then used to calculate fire danger indices for the following day in WIMS and in accord with local site descriptors, (WFAS, 2018b).

This analysis seeks to establish how accurate the 1-day forecasts are across the country and then explore the relationships between the 1-day forecasted fire danger indices and wildfire activity across the conterminous US and compare this with findings from Walding et al. (2018) (Chapter 4).

5.2. Methods

In order to understand the relationships between, firstly, the forecasted and observed NFDRS Fire Danger Indices (FDIs), and secondly, between the forecasted FDIs and wildfire activity across the conterminous US, data processing methods and correlation methods from Walding et al. (2018) (Chapter 4) will be applied to the 1-day forecast FDI data in accord with the observed FDI and wildfire activity data previously presented in Chapter 4. This section will discuss details of the datasets utilised in this study, data processing methods, and the statistical analyses conducted.

5.2.1. Data sources and processing

Fire danger data was sourced from the WFAS data archive for the conterminous USA from the period 2006-2013 (WFAS, 2018d; http://www.wfas.net/index.php/search-archive-mainmenu-92, accessed 21 July 2016). Daily reports from weather stations situated across the country consist of weather observations, derived secondary outputs, and computed fire danger indices. Every day, the WFAS website publishes fire danger maps of the 1-day forecasts and the observed fire danger maps, as well as the constituent datasheets for each of the maps. It is these datasheets that have been accessed and utilised in this study. Fire danger indices (forecasted or observed) are not reconstructed or calculated from separately sourced weather data as the ‘known’ and ‘forecasted’ fire danger conditions, representing the knowledge that is released to the public and utilised by fire managers at those respective points in time is of key focus in this analysis. For the purpose of this study both observed data and 1-day forecasts were collected, formatted, and then expressed as daily means on a 1 x 1° degree grid, which is a grid size consistent with the spatial remit of the fire danger indices (Fosberg and Furman, 1971, Freeborn et al. 2015). Thus, coupling these data with the gridded observed FDI data from Chapter 4, forecasted and observed fire danger data was collated per grid square for each day throughout the time period 2006-2013 across the conterminous USA. The 1-day forecasts of the fire danger indices are based on 1-day fire weather trend forecasts from the NWS whilst the observed fire danger outputs are calculated using recorded observations from each weather station at 1pm LST each day. The number and geographic distribution of reporting weather stations changes from day to day, with the number of reporting stations ranging from ~1500-3000 (See Figure 5.1) for the distribution of daily reports across the USA for this study)

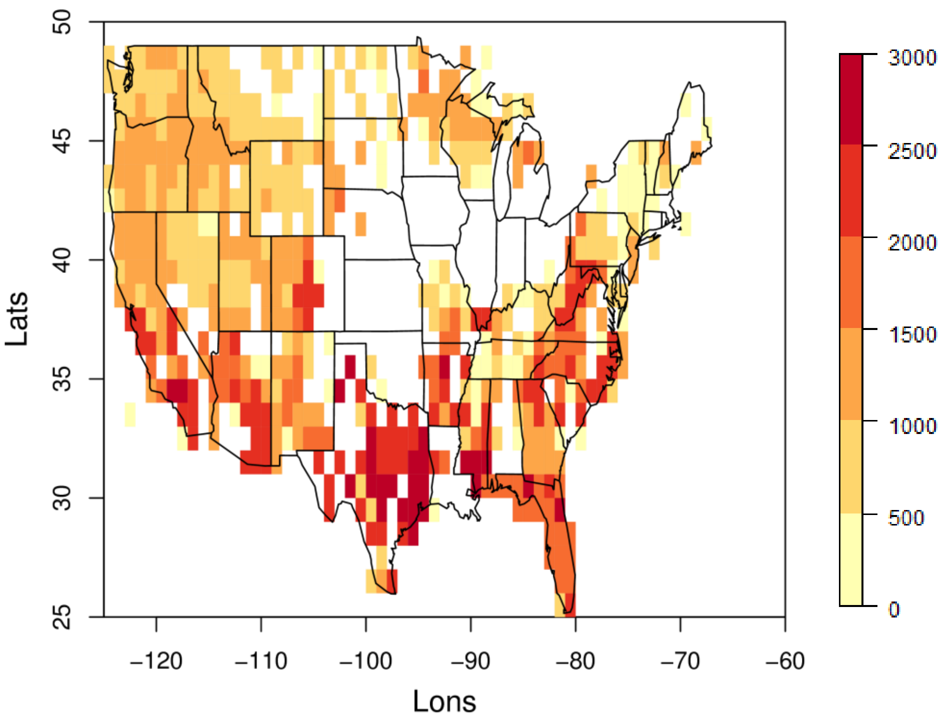

Figure 5.1. Number of daily NFDRS weather station reports from 2006-2013, highlighting the distribution of NFDRS data across the conterminous US.

The forecasted fire danger indices utilized here are the same as those selected in Walding et al. (2018) (Chapter 4), which included the Fire Danger Adjective Rating (FDR, in which for the purpose of this study, the 5 adjective classes, low – extreme, are represented as values of 1-5, respectively), Staffing Level (STL), and Ignition Component (IC). These indices have been chosen for this study based on their public facing nature (FDR), their representation of management resource requirements (STL), and the probability that a firebrand will cause a fire that requires suppression action (IC). By examining these indices a number of aspects of fire danger are represented. The selected ‘end-point’ indices from the NFDRS are the focus of this analysis rather than the secondary fire danger indices such as the Energy Release Component (ERC), the Burning Index (BI), and the Spread Component (SC), because the FDR, STL, and IC are consistently calculated and utilised by fire managers across the country. One of the aforementioned secondary fire danger indices is chosen to derive the STL with percentile breakpoints, and different locations and fire managers may choose different variables to best represent their fire danger conditions on any particular day. Moreover, the STL translates fire danger conditions into an understanding of where a given location sits on the fire danger continuum on any given day and so provides a greater understanding of the known or forecasted fire needs in terms of resource allocation, personnel required and difficulty of control in terms of suppression efforts (Schlobohm and Brain, 2002).

Following the data processing procedure outlined in Walding et al. (2018) (Chapter 4), gridded daily-means of both forecasted and observed FDR, STL, IC data were produced for each day from 2006-2013 for the conterminous US. The same processing techniques were utilised with the USFS Fire Program

Analysis Fire Occurrence Database (FPA FOD) (Short 2015a) to produce gridded monthly-totals in Fire Occurrence (FO) and Final Fire Size (FFS, acres). A number of analyses were then conducted to identify relationships between forecasted and observed fire danger indices and ascertain how accurate the 1-day forecasts are. Furthermore, following the methodology presented in Walding et al. (2018) (Chapter 4), correlations of monthly-mean forecasted FDIs and monthly-totals of FO and FFS were conducted.

Table A5.1 in Appendix V provides further details on the data utilised in this chapter with details on how the data was processed and summarised with clearly stating the variables created in the process for use in the analysis.

5.2.2. Correlation analysis of Forecasted and Observed NFDRS outputs

For each of the three FDIs examined in this study, the 1-day forecast and observed data in each grid square were correlated for all grid squares of the conterminous US, producing maps of, and distributions of correlation coefficients for each FDI. Spearman Rank correlation was utilised based on its ability to relate both discrete and continuous datasets. To further understand how well the forecast and observed indices corresponded to one another, all days and grid squares were considered together with the forecasted vs observed data plotted on heatmaps for each FDI in order to identify where the majority of the fire danger data occurred along each of the FDI value spectrums. Once this was achieved, a linear regression model of the forecasted and observed data for each FDI was plotted against each of the FDI heatmaps to show the overall relationships between the forecasted and observed indices.

Table A5.2 in Appendix V provides further details on the different steps of the analysis in this chapter with explicit descriptions of the variables used, with details on the statistical techniques used, their definition, their justifications for use, and information on how to interpret the specific outputs from each step of the analysis.

5.2.3. Correlations of forecasted FDIs vs Fire Activity

Following the methodology presented in Walding et al. (2018) (Chapter 4), correlations of gridded monthly-mean forecasted FDIs with gridded monthly-totals of FO and FFS were produced. Spearman Rank correlation was utilised once again due its appropriateness when using discrete and continuous datasets. Maps of correlation coefficients were produced for each forecasted FDI and each metric of fire activity; FO and FFS. In addition the distributions of correlation coefficients were also produced along with heatmaps of the conterminous US highlighting regions where correlations between the forecasted FDIs and FO and FFS were weaker than the corresponding correlations using the observed FDIs presented in Walding et al (2018) (Chapter 4, Figures 4.3 and 4.4).

5.3. Results

Using the methods described above, the relationships between forecasted and observed fire danger indices are examined. Correlation heatmaps between forecasted FDIs and wildfire activity are produced and then contrasted with findings from Walding et al (2018) (Chapter 4).

5.3.1. Correlation analysis of Forecasted and Observed NFDRS outputs

Figure 5.2 shows the spatial distribution of correlation coefficients between forecasted and observed FDIs (FDR, STL, and IC) across the conterminous US. Strong positive correlation coefficients can be seen between the forecasted and observed data across all three FDIs ($p \leq 0.05$, nonsignificant correlations are indicated by grey pixels) with majority of grid squares displaying significant strong positive correlations with coefficients greater than 0.6 across the country.

For the FDR, a small number of grid squares around the country in the Eastern, Southern, Southern California, and Great Basin Geographic Area Coordination Centers (GACCs) exhibit slightly lower positive correlations of 0.4-0.6 (Figure 5.2a). The regions with the highest correlation coefficients can be seen in Northwest, Northern California, and Southwest GACCs. However across the rest of the country and along the eastern seaboard very few grid squares can be found with a correlation coefficient above 0.8. A similar spatial distribution of correlation coefficients can be seen for the STL (Figure 5.2b) however a number of grid squares with correlation strengths above 0.8 can be seen outside of the Northwest, Northern California, and Southwest GACCs in locations in Florida and Arkansas and the Dakotas. The spatial distribution of correlation coefficients for the IC shows a number of regions, including the Northwest, Northern California, Southwest GACCs, and the states of Texas, Tennessee and the Carolinas, displaying correlation strengths greater than 0.8. The spatial distribution also displays a cluster of coefficients with scores of 0.4-0.6 for the IC can be seen to be in the state of Nevada (Figure 5.2c).

Figure 5.3 shows the corresponding distributions of correlation coefficient scores from the correlation maps displayed in Figure 5.2 and highlights that the majority of correlation coefficients scores fall between 0.6 and 0.8 (see orange bars in Figure 5.3). The IC displays the highest number of grid squares with scores great than 0.8, whilst the STL has the greatest number of grid squares with weaker-positive correlations ranging from 0.2 to 0.6.

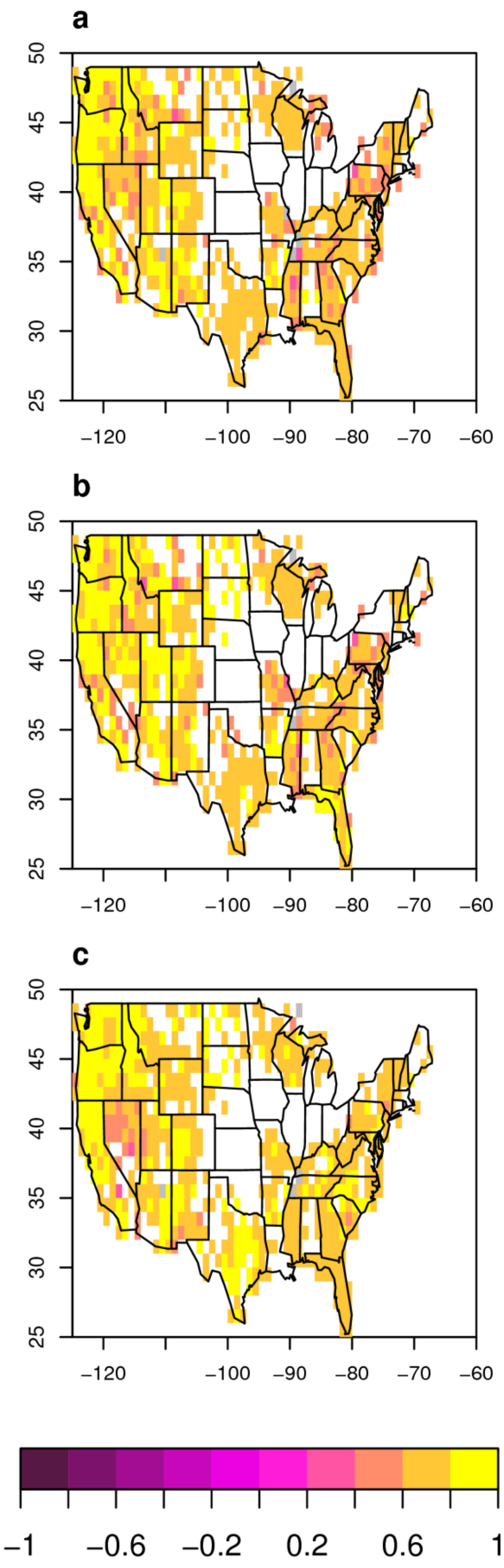

Figure 5.2. Correlation coefficients (Spearman Rank Correlation) of 1x1 degree gridded data for (a) daily-mean forecasted FDR versus daily-mean observed FDR; (b) daily-mean forecasted STL versus daily-mean observed STL, (c) daily-mean forecasted IC versus daily-mean observed IC.

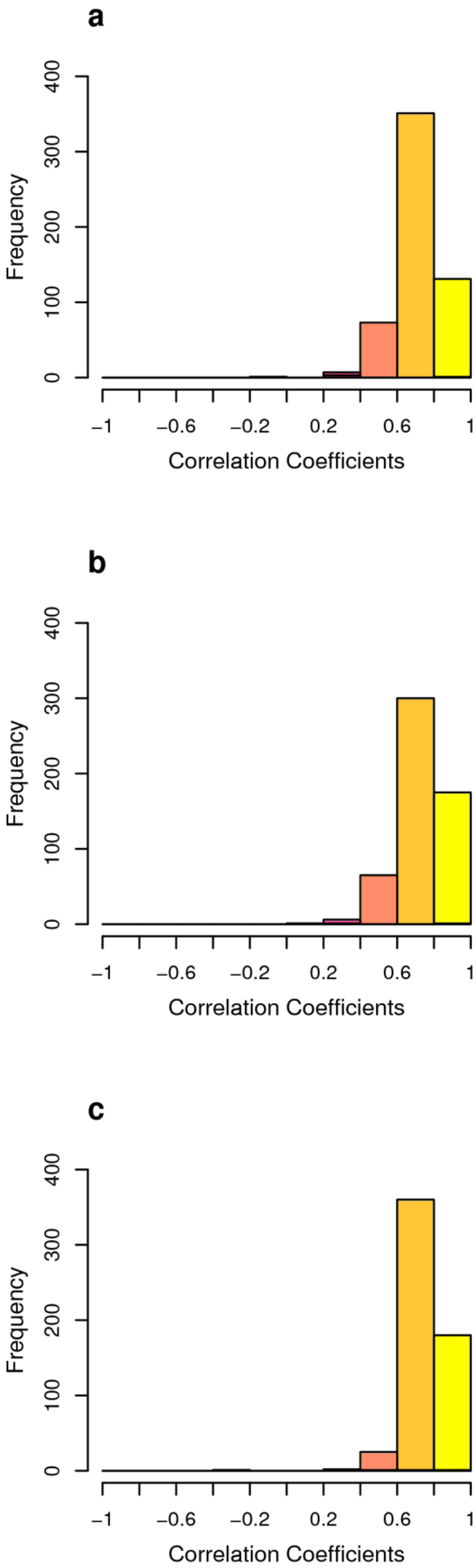

Figure 5.3. Distributions of correlation coefficients (Spearman Rank Correlation) for (a) daily-mean forecasted FDR versus daily-mean observed FDR; (b) daily-mean forecasted STL versus daily-mean observed STL, (c) daily-mean forecasted IC versus daily-mean observed IC.

5.3.2. Heatmaps of Forecasted vs Observed NFDRS outputs

When considering all the data together at the national scale, the heatmaps in Figure 5.4 further display the relationships between forecasted and observed data for each of the FDIs where darker colours indicate where there are higher densities of data with that particular values in forecasted and observed fire danger. For the IC, a concentration of data points are in the lower-end of the index's value spectrum whilst the data points for the FDR and the STL data seem to cluster along spectrum of values and near the whole integer values (an artefact of ordinal data). The heatmaps for each of the FDIs also highlight instances of where the forecasted and observed data appear to diverge from one another, creating an apparent window of forecasting error that spans the whole value spectrum for each of the FDIs.

5.3.3. Linear models of Forecasted vs Observed NFDRS outputs

Figure 5.4 also displays a linear regression model (solid blue line) in addition to the forecasted=observed FDI line (solid black line) representing perfect forecast accuracy. Although the linear model indicates a positive relationship between the forecasted and observed FDIs, the divergence of the linear model from the forecasted=observed FDI lines indicate that the NFDRS outputs (and therefore the models and calculations behind the system) systemically under-predicts high-end FDI values, and over-predicts low-end FDI values.

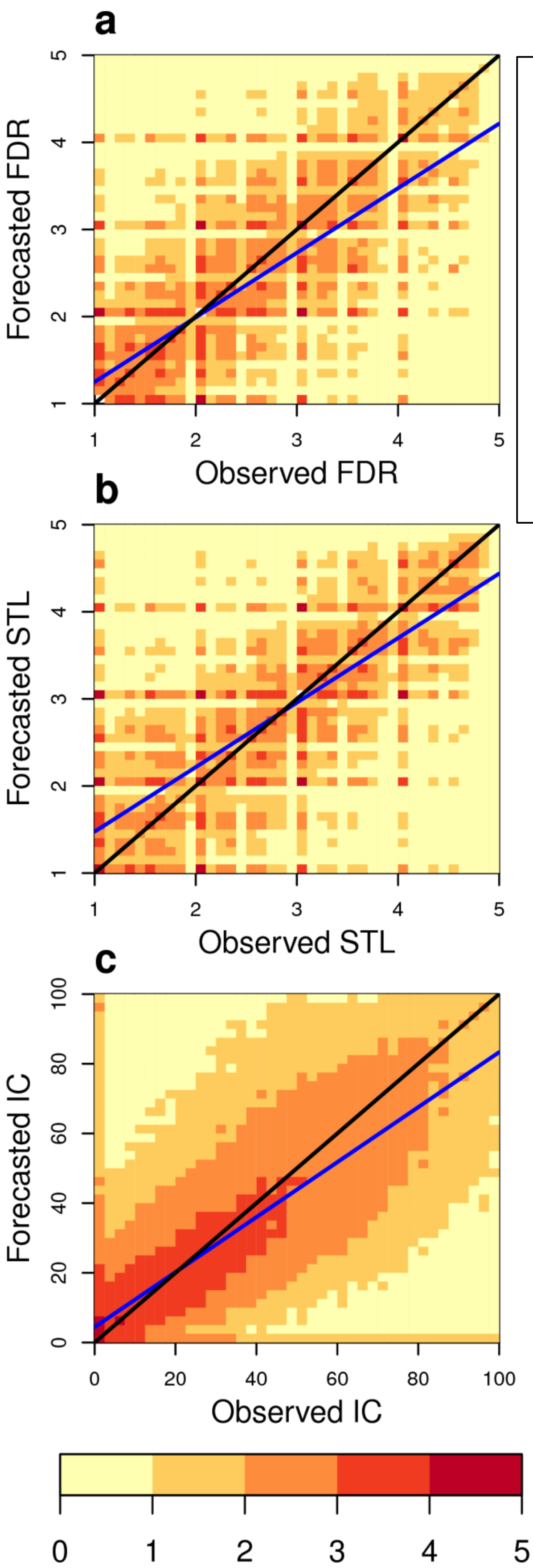

Figure 5.4. Heatmaps indicate where there are higher and lower densities (log10 counts) of data represented by the darkness of the value. In this figure the distribution of the forecasted and corresponding observed FDI values can be seen for (a) daily-mean FDR, (b) daily-mean STL, (c) daily-mean IC, with a y=x line (black line) and a linear model of the relationship between each forecasted and observed fire danger index (blue line).

5.3.4. Correlations of forecasted FDIs vs Fire Activity

Figure 5.5 displays the spatial distribution of correlation coefficients between the monthly-means of each of the forecasted FDIs (FDR, STL, and IC) with monthly-totals of FO and FFS ($p \leq 0.05$, nonsignificant correlations are indicated by grey pixels). When compared with the spatial distributions of correlations between the observed FDIs and FO and FFS from Chapter 4 (Figure 4.3), similar patterns of correlations can be seen but with lower correlation strengths. The Northwest, Northern Rockies, Great Basin, and Northern California GACCs, areas with a considerable number of grid squares with strong correlations with regards to observed FDIs, display significantly weaker correlation with both FO and FFS, and a much smaller number of correlations above 0.75. The rest of the country however show similar patterns to those displayed in Figure 4.3 with weaker positive correlations ranging from 0.25-0.5 being largely present.

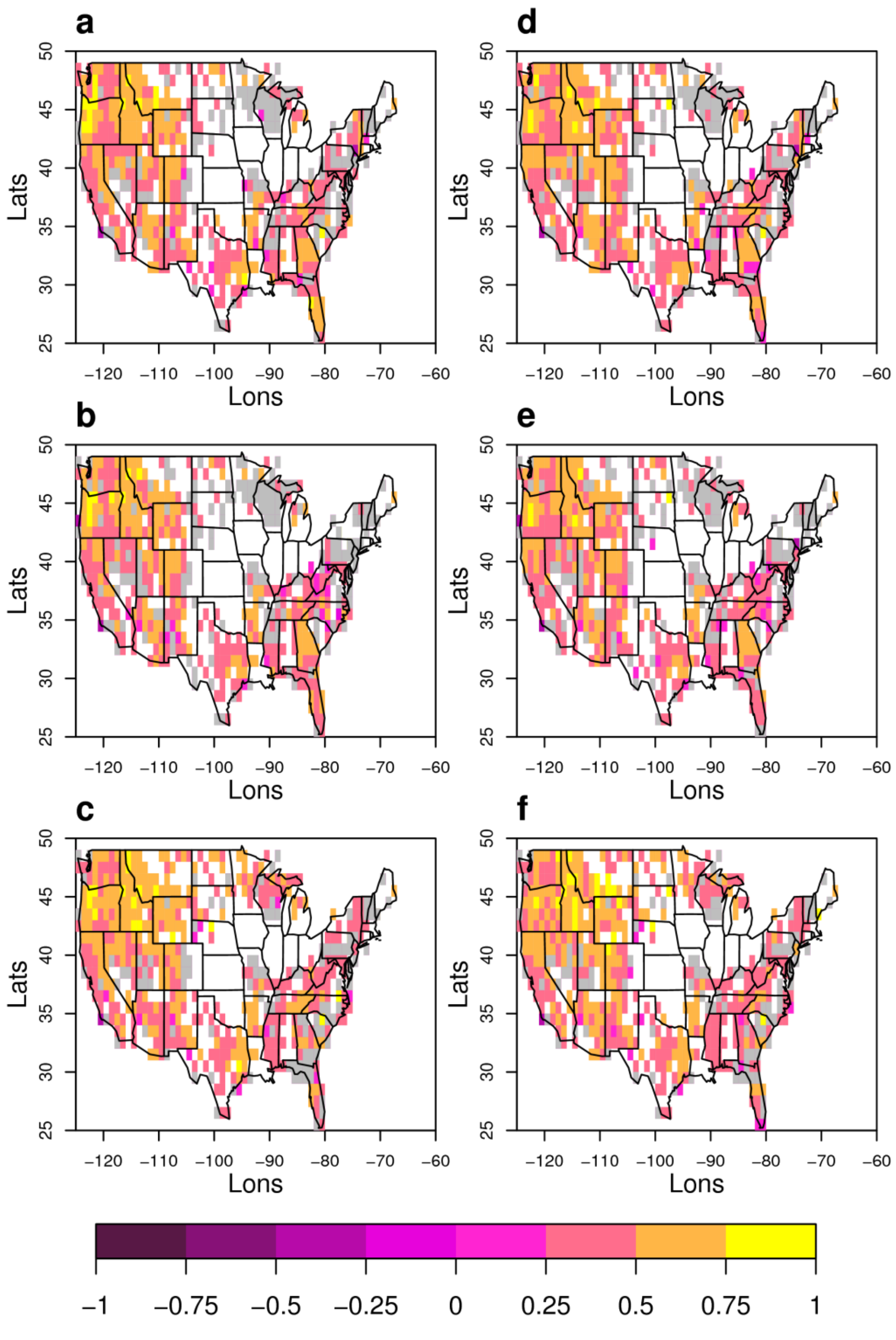

Figure 5.5. Correlation coefficients (Spearman Rank Correlation) of 1 × 1° gridded data for monthly total Fire Occurrence (FO) v. (a) monthly mean forecasted Fire Danger Rating (FDR), (b) monthly mean forecasted Staffing Level (STL), (c) monthly mean forecasted Ignition Component (IC); and monthly total Final Fire Size (FFS) v. (d) monthly mean forecasted FDR, (e) monthly mean forecasted STL, (f) monthly mean forecasted IC. Grey areas represent non-significant correlations (p ≤ 0.05) and white areas represent areas of No Data. The spatial distribution of areas of no data is determined by the absence of reporting weather stations across our study's time period with no correlation being calculated for these areas.

Figure 5.6 shows the corresponding histograms of correlation coefficients from Figure 5.5 and can be once again compared with the histograms of correlation coefficients from the same correlations that were conducted with the observed FDIs from Chapter 4 (Figure 4.4). Across the 6 panels the greatest proportion of coefficient values are between 0.25-0.5 and the proportion of grid squares exhibiting such correlation coefficients is substantially higher when compared to the observed FDI correlations (Figure 4.4). Moreover, the proportion of grid squares displaying correlation coefficients above 0.75 is also vastly reduced for the forecasted monthly-mean FDIs.

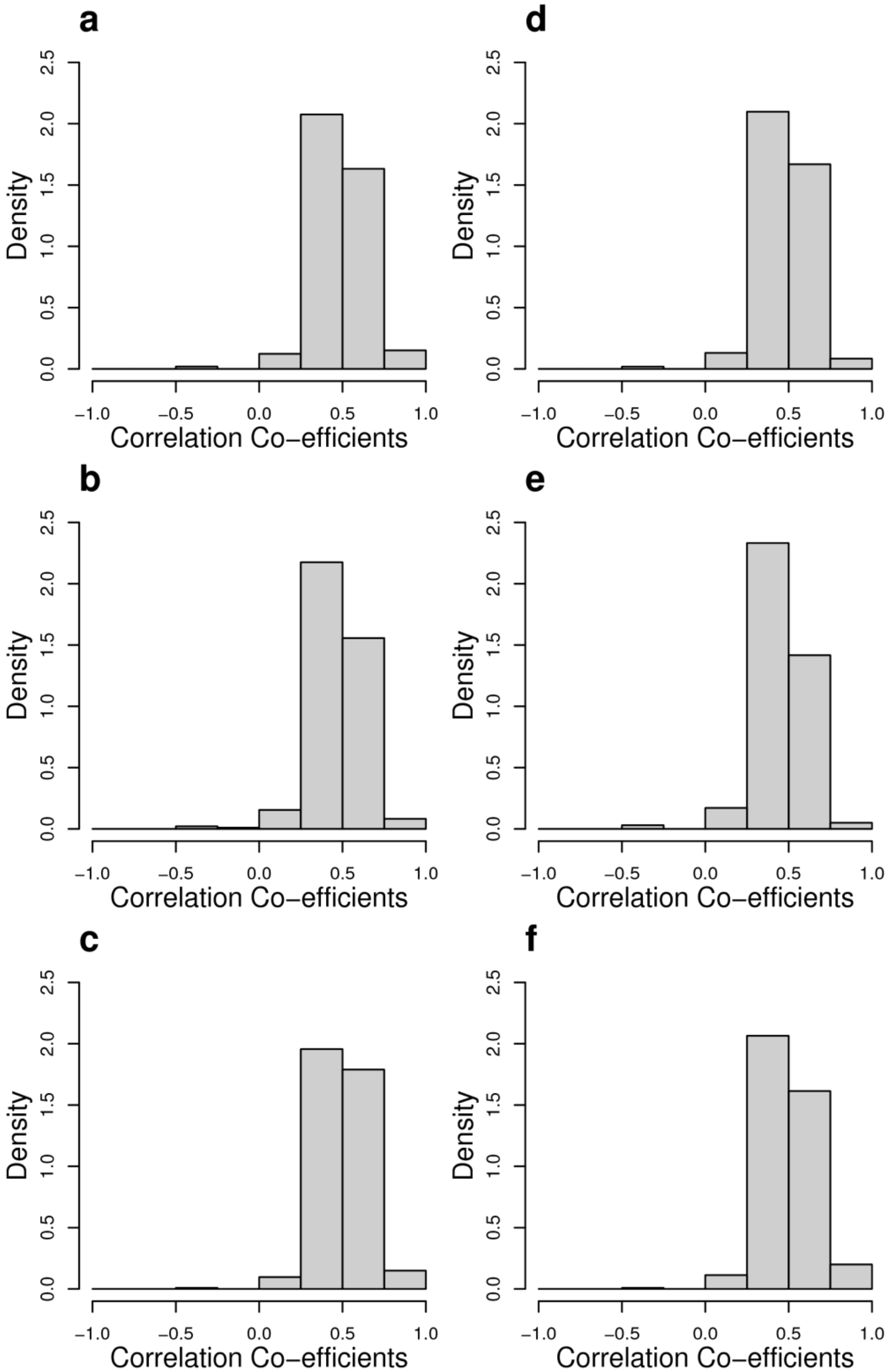

Figure 5.6. Histograms of correlation coefficients (Spearman Rank Correlations) for the corresponding maps plotted in Figure 5.5, which show monthly total Fire Occurrence (FO) correlated with (a) monthly mean forecasted Fire Danger Rating (FDR), (b) monthly mean forecasted Staffing Level (STL), (c) monthly mean forecasted Ignition Component (IC); and monthly total Final Fire Size (FFS) correlated with (d) monthly mean forecasted FDR, (e) monthly mean forecasted STL, (f) monthly mean forecasted IC.

Figure 5.7 indicates where the correlations between forecasted FDIs and FO/FFS are weaker than the correlations between the observed FDIs and FO/FFS across the conterminous US. Across the 6 panels, on average 68% of grid squares exhibited weaker correlations between the forecasted FDIs and FO/FFS, with areas within the Northwest, Northern Rockies, Great Basin and Northern California GACCs showing consistently weaker correlations across the 3 FDIs. The Eastern, Southern and Southwest GACCs also display regions where the correlations between the forecasted FDIs and FO/FFS are weaker than the correlations with the observed FDIs but these form more of a patchwork mosaic against grid squares which do not display weaker correlations. Regions that do not display weaker correlations with forecasted FDIs include southern Montana, Wyoming, northern Colorado, Florida, western Texas, and parts of New Mexico.

Figure 5.7 also displays the difference in correlation strength for each of the grid squares across the conterminous US when comparing Figure 5.5 and Figure 4.3. Positive values indicate larger differences between correlation strength and indicate weaker correlations between the forecasted FDIs and FO/FFS. Areas such as southern Oregon, northern California and northern Nevada display the largest differences in correlations between the 3 forecasted FDIs and FO (Figure 5.7a, b, c), with the same being shown for FFS (Figure 5.7d, e, f) but at lower magnitudes of difference. Regions across the rest of the country however display very small differences in correlation strength with the majority of differences ranging from 0-0.1.

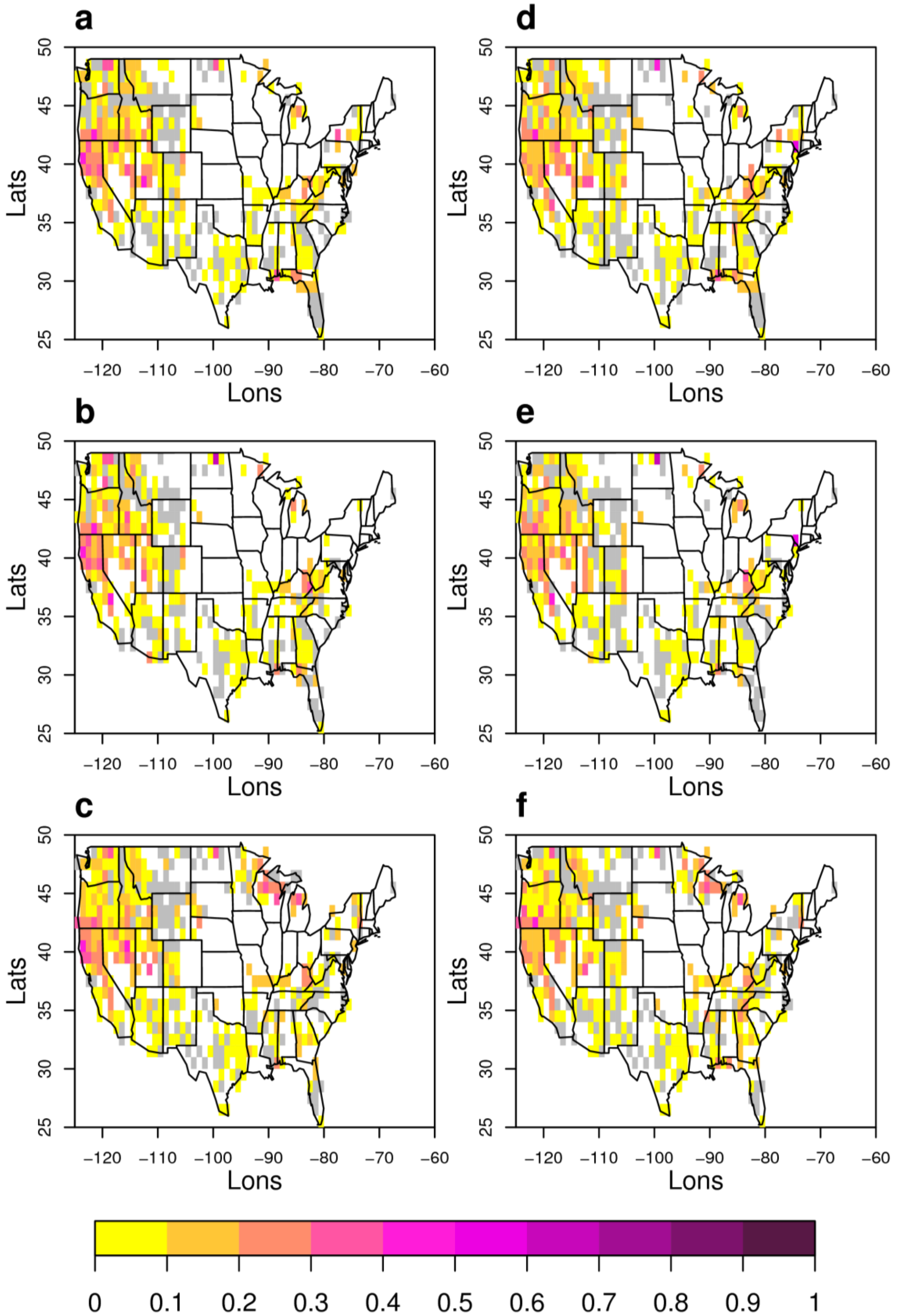

Figure 5.7. Difference in correlation strength between the forecasted FDI and Fire Activity and the observed FDI and Fire Activity (i.e. correlation coefficients in Figure 5.5 minus the coefficients in Figure 4.3), highlighting regions that display weaker correlations between forecasted FDIs vs Fire Activity, than observed FDIs vs Fire Activity (where; FDR: a, d; STL: b, e; IC: c, f; FO: a, b, c; FFS: d, e, f). Areas that do not display weaker correlations are greyed out.

5.4. Discussion

From the analyses presented in this chapter, overall good correspondence between forecasted and observed FDIs can be seen across the majority of the conterminous US over the time period 2006-2013. However some areas can be seen to show weaker relationships between indices, most notably in northern Nevada with the forecasting of the IC. Other areas across the country also show weaker correlations however they appear more sporadically distributed within the Northwest, Northern Rockies, and Eastern GACCs. Additionally, when all of the grid squares in Figure 5.2 are examined in aggregate it can be seen that there are multiple instances in which the 1-day forecasts either over- or under-predict the fire danger conditions, across all 3 FDIs; the FDR, STL, and IC (Figure 5.4). The over-prediction of fire danger indices occurs when the forecasted fire danger is higher than the observed fire danger, and the under-prediction of fire danger occurs when the forecasted danger is lower than the observed fire danger. Divergence from the forecasted=observed lines from the linear models in Figure 5.4, indicate systematic over-prediction of low-end FDI values and under-prediction of high-end FDI values in particular. Forecasting fire danger is an integral tool in fire management, facilitating successful suppression action, appropriate resource allocation and prioritisation, and effective fuel management strategies, all whilst ensuring fire fighter and public safety (Countryman 1972, Alexander and Cruz, 2013).

When it comes to fire behaviour and fire danger models, perfect accuracy is rarely attained (Scott et al. 2014) and also depends upon the knowledge and skill of the user with accuracy ranging substantially between different model types. For instance, Cruz and Alexander, (2013) have identified that mean percentage error in 49 rate of spread models varied between 20 and 30% and highlighted that only 3% of rate of spread predictions examined fell within a ±2.5% error window. From Albini, (1976), there are 3 sources of forecast and model error pertaining to fire behaviour calculations. These include a lack of model applicability, a model's internal inaccuracy, and errors associated with input values. Even though these 3 sources of error are in connection with fire behaviour models such as empirical or physics-based models estimating rates of spread, parallels can be drawn towards models of fire danger as fire danger utilises fire behaviour models such as Rothermel's (1972) rate of spread model in its fundamental foundation (Deeming et al. 1977, Burgan, 1988). Regarding these 3 sources of error and our findings here it can be ascertained that both the applicability of the model and any internal errors regarding the models in the NFDRS can be somewhat 'ignored'/resolved as the findings from Walding et al. (2018) (Chapter 4) highlight strong relationships between the observed FDI tested against Fire Activity across the country. The fundamental assumptions of the NFDRS, which could account for some of the discrepancies shown in Chapter 4 between FDI and fire activity, however would be consistently applied here across the calculation of both observed fire danger indices and the forecasted fire danger indices. Therefore discrepancies between forecasted and observed FDIs would be from another source of error rather than the model's internal inaccuracy.

I suggest that potential sources of error regarding the over- and under-prediction of forecasted FDIs presented in this chapter may be owing to errors in input variables, namely estimates of; i) forecasted fire weather conditions; ii) the subsequent derived fuel state; and iii) the timing of daily observations.

i) The forecasted FDIs are calculated using forecasted fire weather conditions for either specific weather stations, and their Fire Danger Rating Areas (FDRAs), or wider fire weather zones across the USA. The NWS forecasters use the observed fire weather variables entered into WIMS for each of the reporting fire weather stations across the RAWS network and apply forecasting trend analyses to produce estimates of fire weather. These fire weather forecasts are then reprocessed through WIMS together with site descriptor information entered by land managers to produce forecasted fire danger outputs for each of the reporting weather stations (NWS, 2017). The trend analyses applied by the forecasters from the NWS may then be the point of difference in the construction of the forecasted fire danger indices from the observed fire danger indices, as the model assumptions will be consistent across both sets of calculations, and the site descriptors remain constant for each reporting weather station.

ii) How fuels respond to daily fluctuations in the fire weather condition and how this is captured within the NFDRS also needs to be considered. Fuel models in the NFDRS are simulated fuel complexes for which all the fuel descriptors required by the mathematical fire spread model (Rothermel 1972) are supplied. These descriptors include the volume, size, weight, type, depth, surface-to-volume ratio as well as other properties of the fuel bed (Schlobohm and Brain, 2002). There are six general classes of fuel based on the predominant surface fuels; marsh grasses and reeds; lichens and mosses; grasses and forbs; shrubs, brush and tree reproduction; trees; and slash. From these categories, some are broken down to produce 20 different fuel models, each with a 1978 and 1988 version based on the sets of improvements implemented in the 1988 revision of the NFDRS (Burgan, 1988, Schlobohm and Brain, 2002).

For instance how a given fuel will respond to changes in fire weather will vary based on the ecosystem present at a given location. For example, grass dominated ecosystems cure at a much more rapid rate than litter beds in densely compacts conifer forests and therefore would respond more rapidly to changes in relative humidity (%) (Graham, McCaffrey, and Jain, 2004). Because fuel moisture is a key component in the calculation of specific fire danger indices such as the IC, SC, and ERC, the ability of the chosen fuel model, at a given location, to interact with 1-day fire weather forecasts and represent the state of real vegetation and litter at the location on a daily timeframe is key. How well any of the fuel models in the NFDRS capture the true fuel at each reporting location however, is a topic of considerable debate (Jolly, 2018, pers comm) and this is likely to be a large contributing factor to some of the discrepancies and differences in correlation strength between observed and forecasted FDIs vs FO/FFS in Figure 5.7.

This issue is highlighted by exploring the regions of the US that show no decrease in correlation strength between forecasted and observed FDIs and FO and FFS which include most notably, southern Montana, Wyoming, northern Colorado, Florida, western Texas, and parts of New Mexico. According to the NFDRS static fuel model map (Figure 5. 8, WFAS 2018c) these regions appear to be dominated by fuel models that are designed to represent Western Perennial Grasses (Fuel Model L) (western grassland ecosystems dominated by perennial grasses with stable fuel amounts from year to year), Pine Grass Savannahs (Fuel Model C) (open pine stands dominated by perennial grasses with enough needle litter to contribute to fuel loading) and Western Pines (Fuel Model U) (ecosystems dominated by pine species that shed lower branches, to remove ladder fuels and are therefore dominated by grass fuelled understory fires) (see Figure 5.8). I suggest that the apparent lack of differences in the correlations in these regions may be owing to the ability of the assigned fuel models to respond more realistically to daily forecast fluctuations in the derived fuel state in response to changes in fire weather. Such that in these cases these fuel models at these locations must better portray the true fuel conditions.

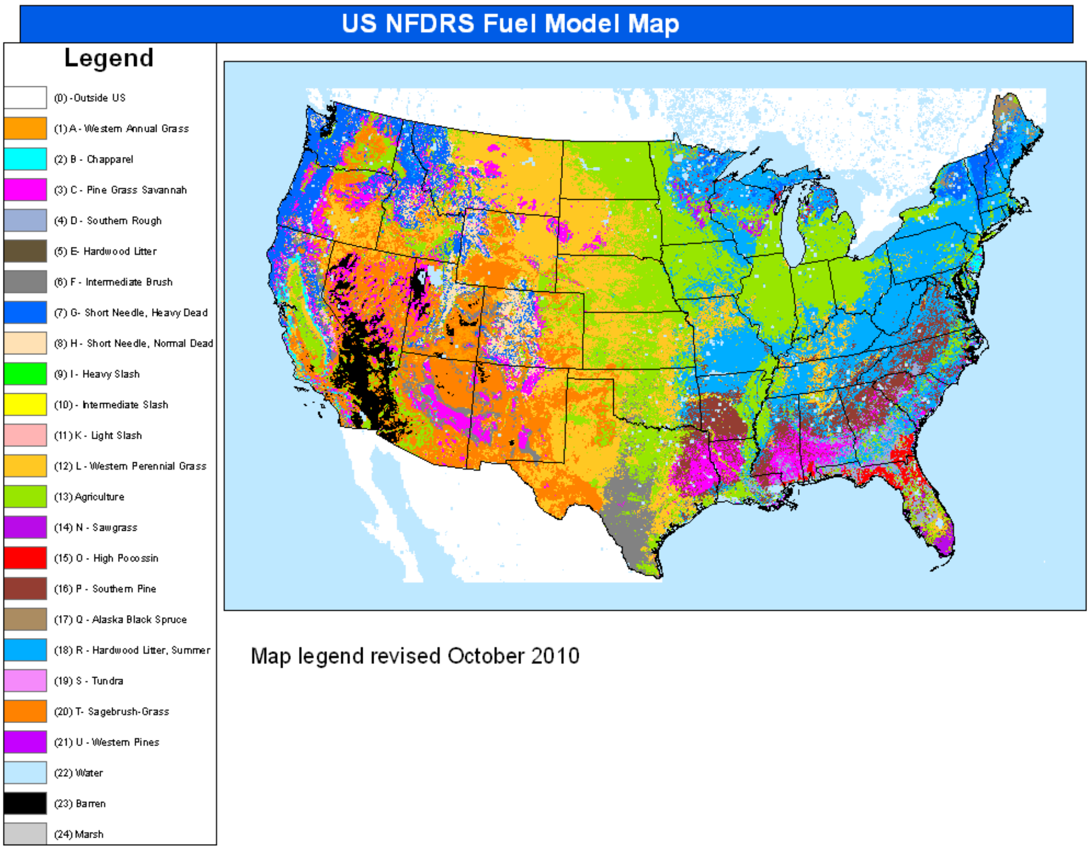

Figure 5.8. NFDRS Static fuel map from the Wildland Fire Assessment System (WFAS, 2018c).

In contrast, regions such as southern Oregon, northern California and northern Nevada, which display the largest differences in correlations (Figure 5.7), occur in Fuel Model G: ‘Short needle, heavy dead’ that represents dense conifer forests where there is heavy accumulation of litter and downed wood material and Fuel Model B ‘Chaparral’ (volatile rich shrub ecosystems).

In the case of Fuel Model G; dense litter and downed wood will take longer to reach equilibrium moisture content with the air and will thus be is less responsive to rapid changes in relative humidity. Hence the coupling of these fuel model descriptors with daily forecasts at a single time during the day are less likely to be as accurate as more rapidly curing fuels i.e. Fuel Model L (Western Perennial Grasses). Regions using such fuel models as part of the NFDRS might benefit by considering 7-day forecast windows that track longer time windows of changes in relative humidity and consider their effects on the moisture content of thicker litter layers. Hence 1-day forecasts might not be well suited to predicting fire danger in this fuel model.

The regions with the next largest difference in correlation are those that use Chaparral fuel models (Fuel Model B). It is well known that even today our ability to predict fire spread in these fuel types is limited. Chaparral fuels contain a dead fraction however, a significant of volume of their easily ignitable fuel is live (Weise et al., 2016) moreover, chaparral fuels are considered to carry crown fire and not surface fires, of which the latter is the key consideration of the NFDRS. The NFDRS utilises the Rothermel fire spread model (Rothermel, 1972), that is not primarily designed for live fuels and assumes that a fire will spread in absence of either wind or slope in fine and dead fuels. These factors likely cause erroneous estimates for Chaparral fuels, where in reality the mixture of live and dead fuel components means that these systems produce larger energy release (Weise et al. 2016) than is estimated by the NFDRS, implying that it will likely be captured poorly in ERC outputs and subsequent derived FDIs (STL and FDR). Wind has also been found to be one of the most significant influences that determine fire spread in live Chaparral fuels (Weise et al. 2016). The regions that show large correlation differences are known to have a strong relationship between fire occurrence and specific weather patterns (van Wagtendonk and Fites-Kaufman, 2006). Here the presence of the Pacific-High-Post-Frontal weather system causes strong north to northwest winds in northern California causing a foehn effect causing strong winds to blow down slope (van Wagtendonk and Fites-Kaufman, 2006). Such weather systems are not well built into FDIs and coupled to the strong linkage between wind phenomena and Chaparral fire spread implies that the NFDRS likely struggles to provide accurate prediction for regions containing this fuel model.

iii) A potential source of inaccuracy in forecasting is the time at which the weather observations and fire weather calculations are taken. Daily observations of fire weather at each reporting weather station are conducted at 1pm LST. This is the time of day considered to best aid the manual collection and calculation of fire weather variables in WIMS as it is after lunch (Jolly, 2018 *pers comm*) and because the fuel will have had the morning to dry (Skowronski, 2018 *pers comm*). However, 1pm is not necessarily the time at which the fuel is most conducive to fire nor does it consider conditions prior to or after this time, which are also critical to the prediction of fire danger. For example, daily variations in fire activity have been shown to be driven by a number of factors including fuel temperature (Countryman, 1966) and diurnal variations in fire weather conditions (Schroeder and Buck, 1970). Therefore this arbitrary point in time (1pm LST) does not accurately represent the daily weather conditions nor the subsequent calculation of fire weather which are key to accurately calculate fuel state and its respective moisture content.

Additional factors need to be explored if we are to understand these diverging correlations. For example, factors such as green up (defined in the NFDRS as the beginning of a new cycle of plant growth, Schlobohm and Brain, 20002), fuel responses to drought conditions and seasonal snow melt. As such it is important to consider whether there is any signal with the time of year inaccuracy appears to peak or reduce through as well as examining whether such variability corresponds to the national fire season (typically the months from March to October). If seasonal trends in forecasting inaccuracy and fire activity can be identified and correlated, the effectiveness of the NFDRS as an operational tool could be better explored.

5.5. Conclusion

From the results presented in this chapter, it can be determined that the 1-day NFDRS forecasts have a strong correspondence with observed FDIs across the USA in the majority of locations. However, this chapter also discussed that in instances where fire weather forecasts are inaccurate, this could be based on NWS trend forecasting as well as issues with the time at which forecasts are made. Additionally areas with certain fuel models appear not to correspond as well with wildfire activity in specific regions due to the more complex nature and interaction of these fuel descriptors with fire weather estimates.

In the following chapter the data utilised here are expanded and employed to consider how different forms of forecasting accuracy/inaccuracy vary through the year and across different regions of the conterminous US. Moreover, these trend in forecasting inaccuracy are related to trends in wildfire activity to explore how well these 1-day forecasts work as an operational fire management tool.

“…..It’s just like the West Indies again; once their great names from the 1970s and 80s retired, the whole thing fell apart”

Geoffrey Boycott

Chapter 6: Seasonal and spatial trends in fire activity and the accuracy of the NFDRS 1-day forecasts.

6.1. Introduction

Variations in fuel load and continuity can operate on decadal timescales where antecedent climate has a long-term influence on fuel (Swetnam and Betancourt 1998, Meyn et al. 2007, Flannigan et al. 2009). This compares to seasonal variations and inter-annual climatic changes that influence fuel flammability in terms of fuel state e.g. moisture content and proportion of live vs dead fuel (Westerling et al. 2003, Krawchuck and Moritz 2011). Moreover, changes in ignition are also known to occur throughout the seasons, for example lightning-caused ignitions tend to predominate in the US summer and decline into the autumn (Whitman et al. 2015). These all imply that aspects of fire danger and fire activity may also respond or at least need to perform and/or respond over longer-timescales in order to provide the strongest management of wildfires over the US. As yet the NFDRS does not produce forecasts over longer ranges, these would be of utility for pre-season planning because long-term climatic variations influence fuel by altering fuel load and fuel state over much longer periods than those that operate on daily timescales (Westerling et al. 2003, Westerling 2016).

Roads et al. (2005) suggested the NFDRS currently has low seasonal forecast skill (when studying the western US) and that seasonal forecasts would provide useful information towards developing more comprehensive fire danger rating forecast capabilities. This apparent lack of forecasting capability for this region is at odds with the observation that large wildfire frequency in the region is strongly sensitive to the timing of spring and snow melt (Westerling, 2016). It has been suggested that NFDRS indices have a poor relationship with fire occurrence and final fire size over longer timescales (Roads et al. 2005). This assumption is based on a study of the western US that took 25kmx25km gridded meteorological data and coupled this to Westerling et al.'s (2002) fire counts and burned area data over a 1°x1° grid. In a later paper, Roads et al. (2010) suggest that their longer-term analysis – 7 month forecasts – may give poor correlations because the precipitation parameterization in the weather models needs to be improved. Despite this Roads et al. (2010) indicated some useful correlations between fire occurrence and the NFDRS' IC for northern California, Oregon, northern Idaho, western Montana, Utah and Colorado, which is also the result of Chapter 4 (Walding et al. 2018) that studied at a similar spatial scale for the entire conterminous US.

Despite Roads et al. (2010) suggesting a poor relationship between their forecasted FDIs and fire activity, Chapter 4 has shown that the observed FDIs from the NFDRS do generally well reflect metrics of fire activity but noted that discrepancies remained in different regions of the US. In Chapter 5 the forecasted FDIs were shown to correspond well with the observed NFDRS outputs. However, it was indicated that in certain regions of the US, there were weaker correlations present between forecasted FDIs and metrics of wildfire activity when compared to the correlations between the observed FDIs and fire activity (Figure 5.7). Interestingly, Chapter 5 identified that according to the linear models in Figure 5.4, the NFDRS tended to over-predict low fire danger and under-predicted high fire danger. As such together Chapter 4 and Chapter 5 have indicated that there are both spatial inaccuracies and forecast inaccuracies leading to discrepancies between FDIs and fire activity. It is clear however, that seasonality (e.g. Westerling, 2016) may explain some of the regional discrepancies in the relationships between the FDIs (forecasted and observed) and fire activity. Therefore there is a need to identify trends in the forecasting accuracy of the NFDRS through the year, highlighting how they change seasonally, and relate this to the impact on fire activity.

Based on these challenges and apparent discrepancies, this chapter aims to define the seasonal and spatial trends of extreme over- and under-prediction of fire danger and understand the relationship between these and trends in fire activity. These subsets of daily NFDRS reports are used to spatially consider the amount of over- and under-prediction of fire danger forecasts across the US which are then related to spatial patterns of concurrent wildfire activity. In order to capture the importance of seasonal variations as reflected in 1-day NFDRS forecasts, variations in the over- and under-prediction of fire danger are examined seasonally, and correlated with monthly trends in fire occurrence and final fire size. As such this chapter seeks to address whether the varying amount of forecasting inaccuracy, either in a specific location or at a particular point in the year, has an impact on concurrent fire activity. This is based on the hypothesis that accurate forecasting facilitates the correct, and successful mitigation of fires, suggesting that if there are instances of inaccurate forecasting then there should be notable differences in recorded fire activity. Finally this is then contrasted to what is determined to represent accurate forecasting of fire danger and itself related to fire activity in order to consider whether variance in perceived accurate forecasting impacts fire activity, both across the conterminous US and throughout the year.

6.2. Methods

Based on the findings from Chapter 5, here I compare the estimated accuracy of 1-day forecasted FDIs, and define three subsets of forecasting accuracy; over-prediction, under-prediction, and accurate-prediction, for each FDI (FDR, STL, IC). The spatial and temporal patterns of forecasting inaccuracy and accuracy are then explored for each FDI, and are then compared to spatial and temporal trends in wildfire activity to ascertain whether the different forms of FDI forecast inaccuracy/accuracy coincide with trends in concurrent Fire Activity, both across the whole of the conterminous US and throughout the year.

In this study the term Fire Activity (FA) encompasses both the occurrence of fire (Fire Occurrence, FO), and the final sizes of wildfires (Final Fire Size, FFS, measured in acres). This section will discuss details of the datasets utilised in this study, data processing methods, and the statistical analyses conducted.

6.2.1. Data sources and processing

The same observed and forecasted fire danger data collected for analysis in Chapters 4 and 5, respectively, were used with the USFS's Fire Program Analysis Fire Occurrence Database (FPA FOD) (Short, 2015a). Gridded daily-means of the forecasted and observed FDR, STL and IC data were produced and compared to corresponding gridded daily-totals of fire occurrences and final fire sizes for each day from 2006-2013, for the conterminous US. A range of analyses were then conducted to identify spatial and temporal patterns in forecast accuracy and assess the relationships between forecasting (in-) accuracy and concurrent fire activity.

Table A6.1 in Appendix VI provides further details on the data utilised in this chapter with details on how the data was processed and summarised with clearly stating the variables created in the process for use in the analysis.

6.2.2. Forecast Inaccuracy

From the heatmaps presented in Chapter 5 (Figure 5.4), clear instances of over- and under-forecasted fire danger indices were observed. From this subsets of accuracy and inaccuracy in FDIs were determined. The over-prediction of fire danger indices occurs when forecasted fire danger is higher than the observed fire danger, and the under-prediction of fire danger occurs when forecasted danger is lower than the observed fire danger. Here I take perfect forecasting accuracy as being expressed as the 1-day forecast equalling the observed value for each FDI, e.g. a line of y=x. A threshold of ± 2 Standard Deviations from the mean difference between forecast and observed values was utilised to define the upper and lower boundaries of three subsets of forecast accuracy (Figure 6.1, dashed lines, respectively).

By choosing to consider data falling more than ± 2 Standard Deviations from the mean the aim was to capture and explore instances of extremely inaccurate forecasting. Assuming a normal distribution, 95.45% of the values in a distribution should lie within 2 Standard Deviations from the mean, therefore I aim to highlight here extreme instances of inaccurate forecasting that may lead to under preparation of or excess infrastructure being prepared for usage as choices based on extreme inaccurate FDIs should then to impact upon fire activity.

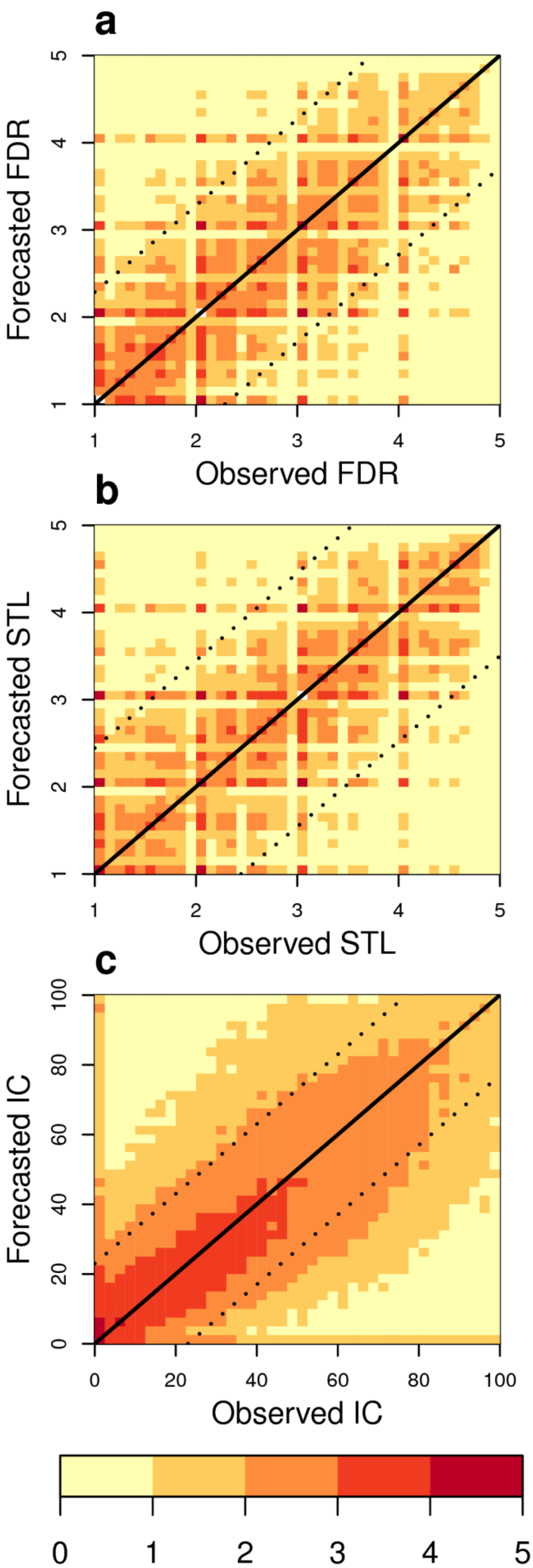

Figure 6.1. Heatmaps (log10 counts) of instances where the 1-day forecasted and corresponding observed fire danger indices fall into each forecast vs observed value pair for (a) daily-mean FDR, (b) daily-mean STL, (c) daily-mean IC, with a y=x line (solid black line), ± 2 Standard Deviations of the mean difference between forecast and observed values for each FDI (upper, and lower dashed black line, respectively).

6.2.3. Determining spatial patterns and temporal trends in Fire Activity and Forecast Inaccuracy

To identify spatial patterns in forecast accuracy the total number of days of over- and under- forecasting was calculated for each grid square across the time period 2006-2013 for the conterminous US and then represented as a percentage of the total number of days of reporting per grid square. These percentages were calculated relative to the total number of reports per FDI as the sizes of the subsets across the three FDIs are not consistent (Table 6.1) owing to inconsistent reporting through the WIMS-WFAS system across the conterminous US. These percentages were calculated for each of the three FDIs, resulting in six maps identifying regions where the highest levels of over- and under- prediction are in the country (Figure 6.2).

To identify temporal trends in fire activity and fire danger 1-day forecast inaccuracy the monthly-mean variance in FO and FFS was calculated as well as the monthly-mean percentage of reports in each subset of inaccuracy (i.e. over- and under-prediction, respectively) per FDI.

To determine the monthly-mean variance in FO and FFS, daily totals of FO and FFS were calculated nationally for the time period 2006-2013, these were then used to evaluate the daily variance in FO and FFS across the eight years. These daily variances were then used to compute the monthly-mean variance in FO and FFS across the eight years. Chapter 4 has shown that FDIs from the NFDRS relate to wildfire activity across the conterminous US. If fire danger is shown to be less accurately forecasted in time and space, this would be owing to the fire conditions and the fire activity being more unpredictable, harder to forecast, and more variable. Therefore in order to couple fire danger forecast accuracy with a measure of fire activity, I have chosen the monthly mean variance in FO and FFS as the summary statistic to represent concurrent fire activity. By using the variance of fire occurrence and final fire size to represent fire activity trends across the US to better reflect and accord with changes in forecasting accuracy of FDIs, it should be noted that due to the relative low frequency nature of wildfires, with the data being zero heavy due to a high number of days of ‘no fire’, the monthly-mean variance in FO could be more aligned with the monthly-mean count of FO and so serves also as a pseudo fire count.

In order to consider how variable fire danger reporting accuracy is according to seasonal trends and allowing for consideration of fire-season and non-fire-season reporting trends the monthly-mean percentage of the daily FDI reports was calculated for each subset of inaccuracy (i.e. over- and under-prediction). This produced daily total number of over- and under- predictions for each day for each year, which were then aggregated to monthly-mean number of over/under predictions. From this, time-series of monthly-mean percentages of over- and under- forecasted FDIs and monthly-mean variance in FA were produced (Figure 6.3).

6.2.4. Correlations between Forecast Inaccuracy and Fire Activity

Following the identification of spatial and temporal patterns for the different subsets of fire danger inaccuracy and fire activity, I next explored how the different subsets of forecasting inaccuracy relate to concurrent FA. Firstly temporal relationships were examined by correlating (Spearman's rank correlation) the monthly-mean percentages of over- and under- forecasted FDIs (Figure, 6.3b and c) with monthly-mean variance in FA (Figure 6.3a) for each FDI (FDR, STL, IC) amalgamating all the grid square data to represent the national situation (Figure 6.4).

Secondly spatially explicit relationships between FDI forecast inaccuracy and their relationship to FA were considered by correlating (Spearman's rank correlation) each FDI inaccuracy subset with FA for every grid square over the conterminous USA. This produced maps and histograms of correlation coefficients (Figure 6.5-6.10), highlighting statistically significant and insignificant relationships across the USA.

6.2.5. Correlations between Forecast Accuracy and Fire Activity

Using the same methods as described above, subsets of accurate forecasting were defined, for each of the three FDIs: FDR, STL, and IC. Accurate forecasts were defined as reports that were within the +/- 2 Standard Deviations threshold from the mean difference in forecasted-observed FDI. Monthly-mean percentage of reports of accurate forecasting were calculated for each FDI in accord with the subsets of forecast inaccuracy to produce a time-series of the amount of accurate forecasting for each FDI. This then allowed the correlation (Spearman's rank correlation) of forecast accuracy and fire activity both with all data amalgamated together to represent the national situation and across different regions of the conterminous US (Figure 6.11 and 6.12).

Table A6.2 in Appendix VI provides further details on the different steps of the analysis in this chapter with explicit descriptions of the variables used, with details on the statistical techniques used, their definition, their justifications for use, and information on how to interpret the specific outputs from each step of the analysis.

6.3. Results

6.3.1. Forecasting Accuracy and Inaccuracy

As expected, ~5% of all FDI 1-day forecasts are classified as inaccurate, following the threshold of ±2 Standard Deviation from the mean difference between forecast and observed values, indicating near-normal distributions of error. Table 6.1 gives details for the subsets of accuracy for each of the FDIs. It can be seen that for the FDR 1.91% of forecasts were determined to have over-forecasted the FDR and 2.48% had under-forecasted the FDR. For the STL, 4% and 2.16% of forecasts were deemed to have over- and under-forecasted the STL, respectively. For the IC, 2.34% and 3.12% of forecasts were deemed to have over- and under-forecasted the IC, respectively.

Table 6.1. Details of the subsets of accurate and inaccurate forecasting created for each FDI from the forecasted=observed line ±2 Standard Deviations lines highlighted in Figure 6.1.

Subset	Description	Subset Size
FDR Over-prediction	Above the +2 Standard Deviation threshold above the forecasted=observed FDR line (Upper dashed line, Figure 6.1a) *(Forecasted FDR > Observed FDR)*	13,487 *(1.91%)*
FDR Under-prediction	Below the -2 Standard Deviation threshold below the forecasted=observed FDR line (Lower dashed line, Figure 6.1a) *(Forecasted FDR < Observed FDR)*	17,524 *(2.48%)*
FDR Correct-prediction	Within ±2 Standard Deviations of the forecasted=observed FDR line (Black line, Figure 6.1a)	674,584 *(95.6%)*
STL Over-prediction	Above the +2 Standard Deviation threshold above the forecasted=observed STL line (Upper dashed line, Figure 6.1b) *(Forecasted STL > Observed STL)*	25,964 *(4.00%)*
STL Under-prediction	Below the -2 Standard Deviation threshold below the forecasted=observed STL line (Lower dashed line, Figure 6.1b) *(Forecasted STL < Observed STL)*	13,987 *(2.16%)*
STL Correct-prediction	Within ±2 Standard Deviations of the forecasted=observed STL line (Black line, Figure 6.1b)	608,871 *(93.9%)*
IC Over-prediction	Above the +2 Standard Deviation threshold above the forecasted=observed IC line (Upper dashed line, Figure 6.1c) *(Forecasted IC > Observed IC)*	16,777 *(2.34%)*
IC Under-prediction	Below the -2 Standard Deviation threshold below the forecasted=observed IC line (Lower dashed line, Figure 6.1c) *(Forecasted IC < Observed IC)*	22,323 *(3.12%)*
IC Correct-prediction	Within ±2 Standard Deviations of the forecasted=observed IC line (Black line, Figure 6.1c)	676,672 *(94.5%)*

6.3.2. Spatial patterns and temporal trends in Fire Activity and Forecast Inaccuracy

By considering these cases of extremely inaccurate forecasting as a percentage of days across 2006-2013 in which each of the forecasted FDIs were either over- (Figure 6.2a, b, c) or, under-predicted (Figure 6.2d, e, f), it can be seen that the maximum percentage of over or under prediction does not exceed 35% and in fact most regions are considerably below this. However, different regions show different patterns of over- and under-prediction for each of the different FDIs. In the case of the FDR, there is more persistent under-prediction in the northwest US, namely in Oregon and Idaho, and over-prediction is more notable across the Sierra Nevada in northern California and Nevada. For the STL, persistent over-prediction is seen across eastern USA but a more notable peak in over-prediction (35%) is seen in Southern Montana. A cluster of grid squares with notable amounts of under-prediction in STL ranging from 15-25% can be seen around the Idaho-Montana boundary area. For IC, a substantial region of over- and under-prediction can be seen around Nevada, Utah, and Arizona, with percentages ranging from 10-20%. In addition to this a cluster of under-prediction can be seen in Utah, with percentages peaking at approximately 25%.

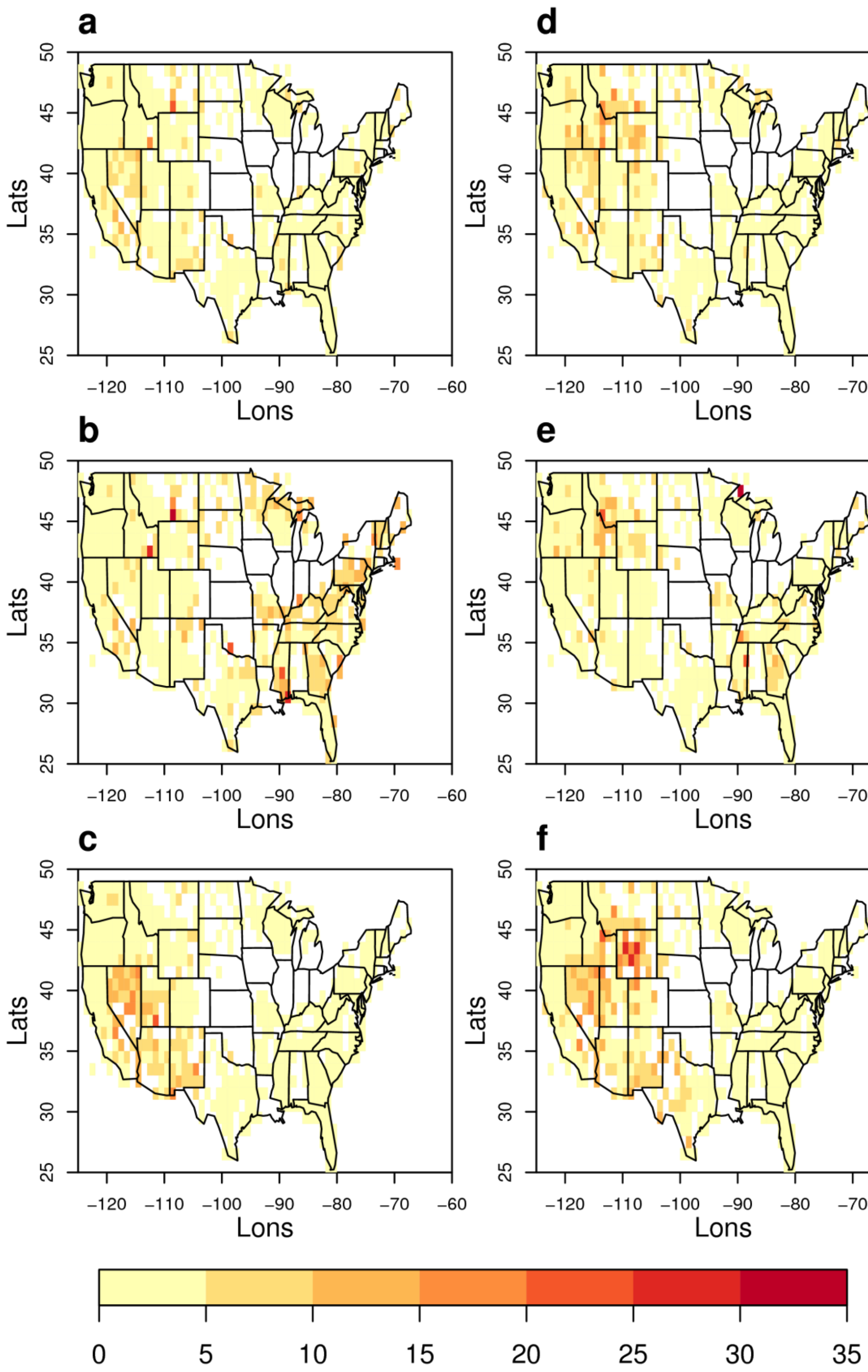

Figure 6.2. Percentage of days from 2006-2013 where FDR (a, d), STL (b, e), IC (c, f), were; Over- (a , b, c) and Under- (e, d, f) forecasted versus the observed FDI ±2 standard deviations.

Figure 6.3 explores the monthly trends in FO and FFS (Figure 6.3a, black and red line, respectively) as well as the monthly trends in over- and under-prediction across the 3 FDIs (Figure 6.3b and 6.2c, solid, dashed, and dotted lines, respectively). Peaks in FO can be seen in spring and in late summer, with FFS also showing an upward trend through summer, peaking in July and August (Figure 6.3a). Trends in over-prediction (Figure 6.3b) vary between the 3 FDIs with the STL displaying consistently high percentages of over-prediction (7-8%) in the winter and spring months, whilst the FDR shows a spike in over-predicting in spring alone, whilst the IC show a less pronounced peak in spring at approximately 3% that then declines to 2% by September. Over-prediction remains at low percentages in the remainder of the year for FDR and IC, however peaks again at the end of the year for the STL. Trends in under-predicting fire danger are shown to peak in both spring and late summer for all 3 FDIs, with the IC exhibiting the highest percentages of under-prediction (3-4%) (Figure 6.3c).

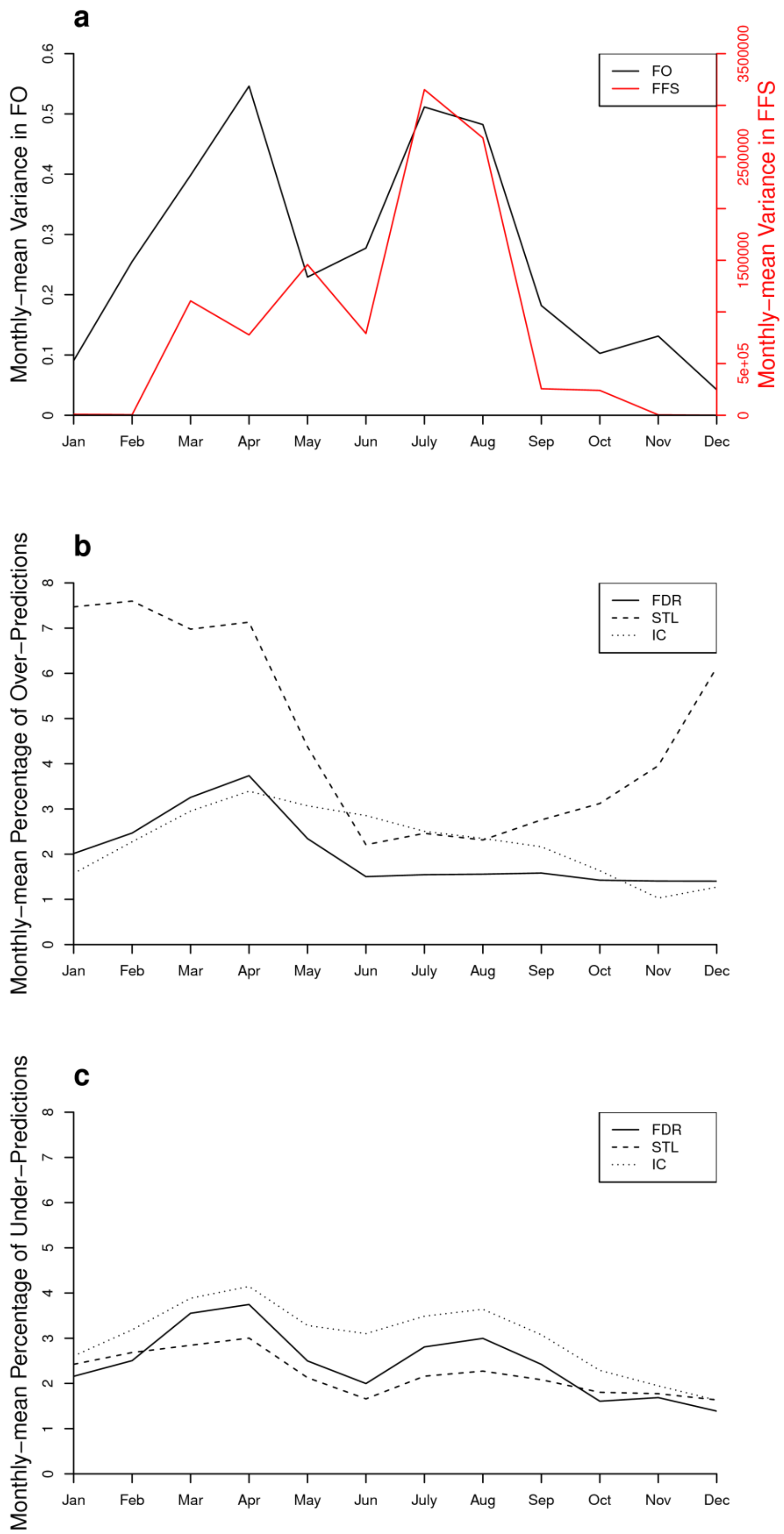

Figure 6.3. Trends in (a) monthly-mean variance in Fire Occurrence and Final Fire Size, (b) monthly percentage of daily forecasts that were over-predicted per FDI, (c) monthly percentage of daily forecasts that were under-predicted per FDI.

6.3.3. Temporal and spatial relationships between Forecast Inaccuracy and Fire Activity

Figure 6.4 takes the aggregated national monthly mean percentages in over- and under-prediction (black and red lines, respectively) per FDI (FDR; 6.4a, 6.4d, STL; 6.4b, 6.3e, IC; 6.4c, 6.4f) and explores how these correlate with monthly FA (FO; 6.4a, 6.4b, 6.4c, and FFS; 6.4d, 6.4e, 6.4f). Figure 6.4a and 6.4d show significant strong positive correlations between monthly mean percentage of under-prediction of FDR and FA with correlation coefficients of 0.87 and 0.65 (FO, FFS, respectively, $p \leq 0.05$). However, there are no significant relationships between the over-prediction of FDR and FA (FO, black line Figure 6a, and FFS, black line Figure 6d, $p \leq 0.05$). Figure 6.4b and 6.4e also show no significant relationships between either the monthly mean percentage of over- or under-prediction of STL with either FO or FFS ($p \leq 0.05$). Finally, Figure 6.4c and 6.4f display significant strong positive relationships between the over- and under-prediction of the IC with both the monthly variance in FO and FFS ($p \leq 0.05$). The correlation coefficients for these relationships range from 0.74 to 0.9 with the relationships between the under-prediction of IC and monthly variance in FO having the strongest relationship (red line Figure 6.4c, $p \leq 0.05$). Table 6.2 details the correlation coefficients for each correlation pair displayed in Figure 6.4.

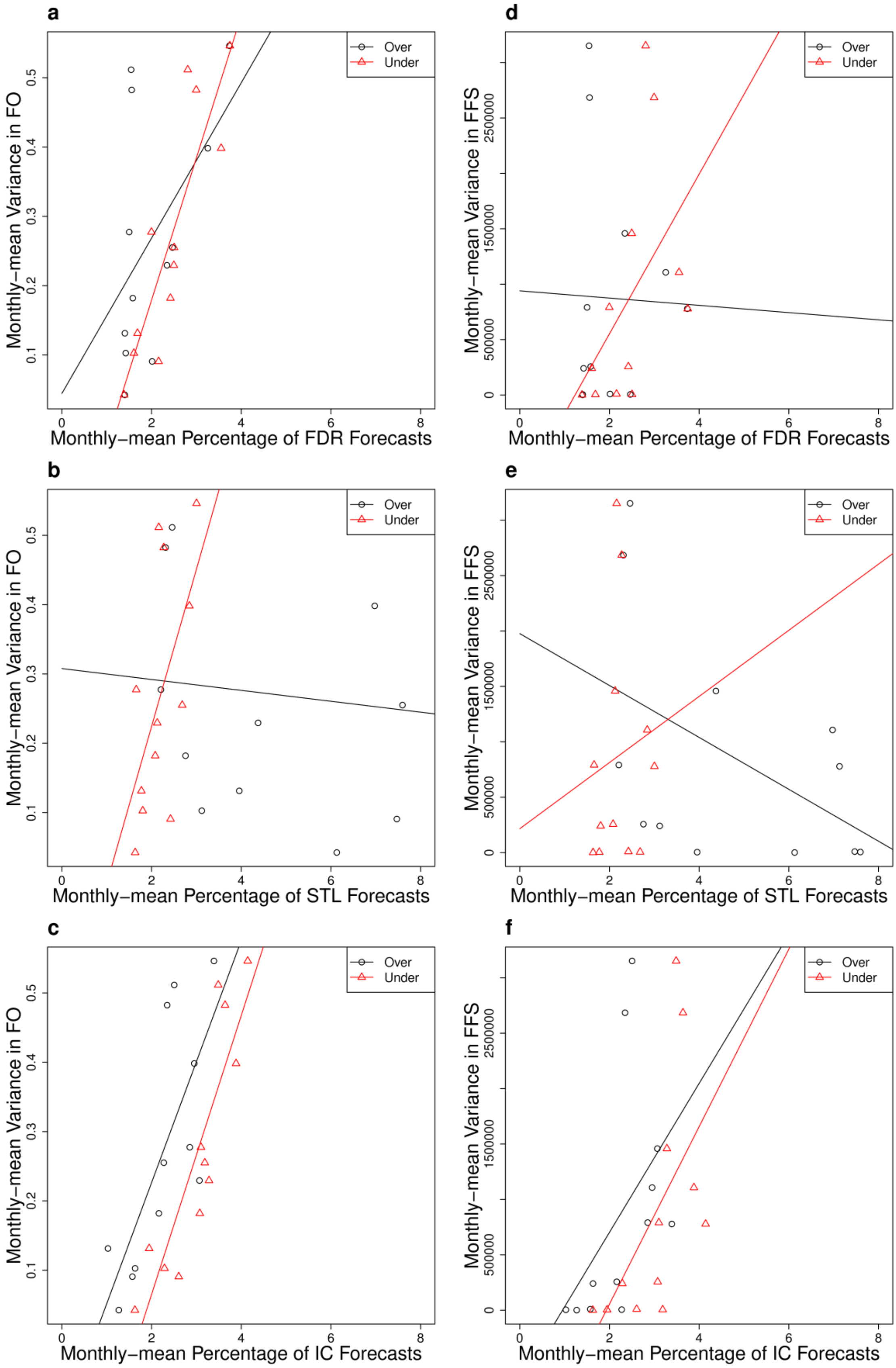

Figure 6.4. Correlations between monthly variance in FO (a, b, c) and FFS (d, e, f), and the monthly percentages of over- and under-prediction (black line, red line, respectively) per FDI (FDR; a, d, STL; b, e, IC; c, f).

Table 6.2. Spearman’s Rank Correlation summary statistic for the correlations displayed in Figure 6.4 and 6.11. Monthly percentage of over-, under, and correct-prediction of fire danger forecasts vs. monthly variance in Fire Occurrence (FO), and monthly variance in Final Fire Size (FFS).

	Over-Prediction	**Under-Prediction**	**Correct-Predication**
Fire Occurrence	FDR: $r = 0.53$, $p = 0.08$, $n = 12$	FDR: $r = 0.87$, $p = 0.04$, $n = 12$	FDR: $r = -0.73$, $p = 0.009$, $n = 12$
	STL: $r = -0.21$, $p = 0.5$, $n = 12$	STL: $r = 0.58$, $p = 0.052$, $n = 12$	STL: $r = 0.14$, $p = 0.67$, $n = 12$
	IC: $r = 0.80$, $p = 0.003$, $n = 12$	IC: $r = 0.92$, $p < 2.2e^{-16}$, $n = 12$	IC: $r = -0.87$, $p = 0.004$, $n = 12$
Final Fire Size	FDR: $r = 0.34$, $p = 0.29$, $n = 12$	FDR: $r = 0.65$, $p = 0.03$, $n = 12$	FDR: $r = -0.5$, $p = 0.1$, $n = 12$
	STL: $r = -0.5$, $p = 0.1$, $n = 12$	STL: $r = 0.33$, $p = 0.3$, $n = 12$	STL: $r = 0.48$, $p = 0.12$, $n = 12$
	IC: $r = 0.74$, $p = 0.008$, $n = 12$	IC: $r = 0.76$, $p = 0.05$, $n = 12$	IC: $r = -0.78$, $p = 0.004$, $n = 12$

Figures 6.5, 6.7, and 6.9 spatially display the correlation coefficients of monthly variance in FO and FFS, and monthly mean percentages in over- and under-prediction per FDI for each grid square across the conterminous US. Figures 6.6, 6.8, and 6.10 display corresponding histograms of the correlation coefficients for each of the preceding map figures. Insignificant correlations between the accuracy of each FDI and FA are shaded out and represented as grey grid squares in each of the correlation maps. To represent these insignificant correlations in the distributions of correlation coefficients (Figures 6.6, 6.8, and 6.10), the corresponding correlation coefficients are shaded grey in each of the histograms.

It can be seen that the majority of locations across the USA display non-significant relationships between the over- and under- prediction of FDR with either the monthly variance in FO or FFS (grey pixels Figure 6.5, $p \leq 0.05$). These insignificant correlations can be seen to represent coefficient strengths from moderate negative correspondence to moderate positive correspondence (grey portion of each of the histograms in Figures 6.6) with only very strong positive or negative correlation coefficients being found to be statistically significant (coloured pixels Figure 6.5). The majority of the grid-squares that show significant correlations indicate that they have a positive correlation with under- or over-prediction of FDR and FO and FS. Moreover, there appear to be more instances of very strong correlations ($r \geq 0.6$) between the under-prediction of the FDR with FO and FFS (Figure 6.6b, 6.6d). Strong positive correlations are distributed widely across the US (Figure 6.5 a, b, c, d). However, areas of negative correlation between FDR and FO and FFS appear to be centred around California (Figure 6.5a, b, c) with the exception of under prediction of FDR with FFS that also shows several pixels across the western states as well as California (Figure 6.5d).

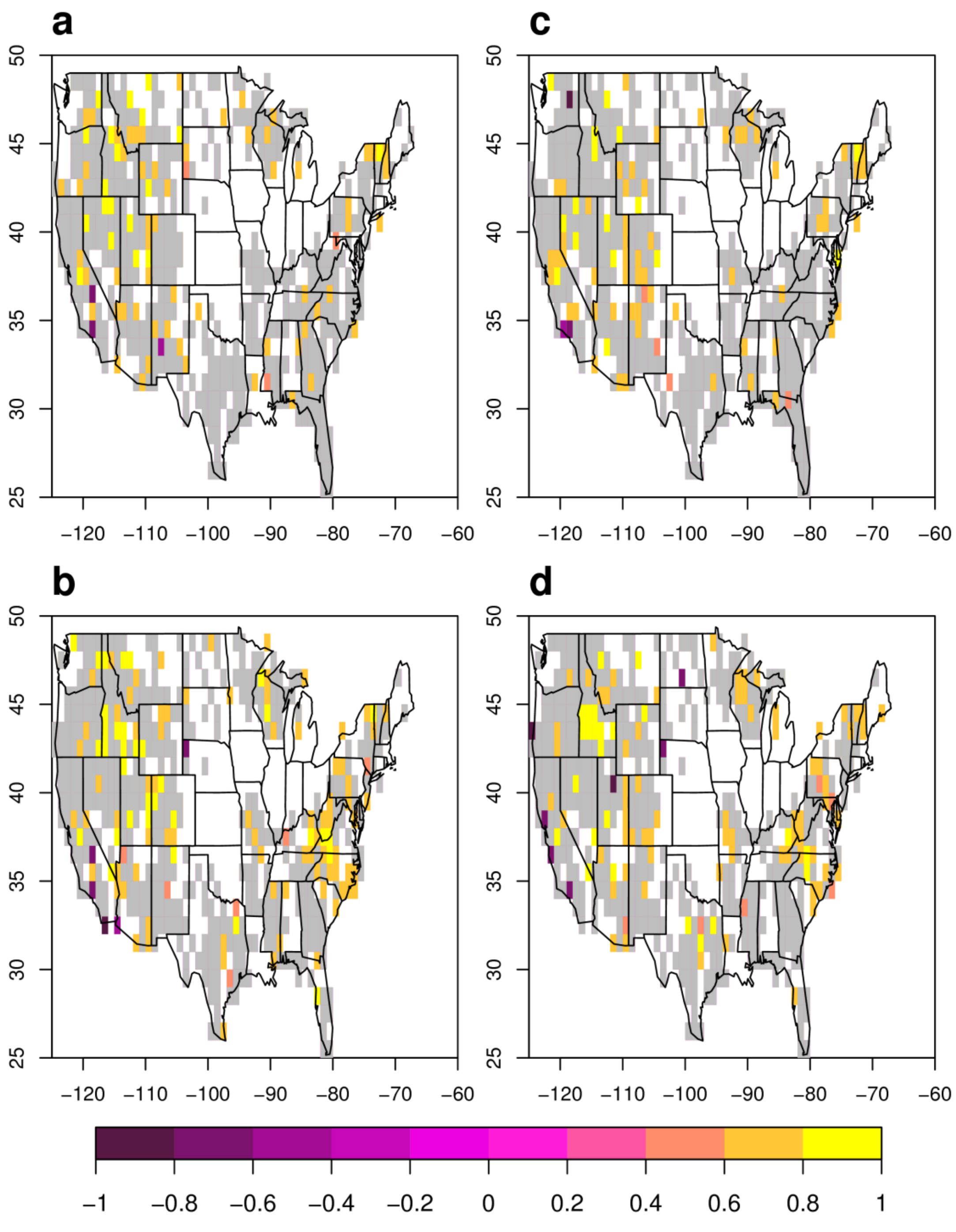

Figure 6.5. Maps of correlation coefficients of monthly percentages of over- (a, c) and under- (b, d) forecasting of FDR vs monthly variance in FO (a, b) and FFS (c, d) per grid square across the conterminous US. Insignificant correlations are represented as grey grid squares (p ≤ 0.05).

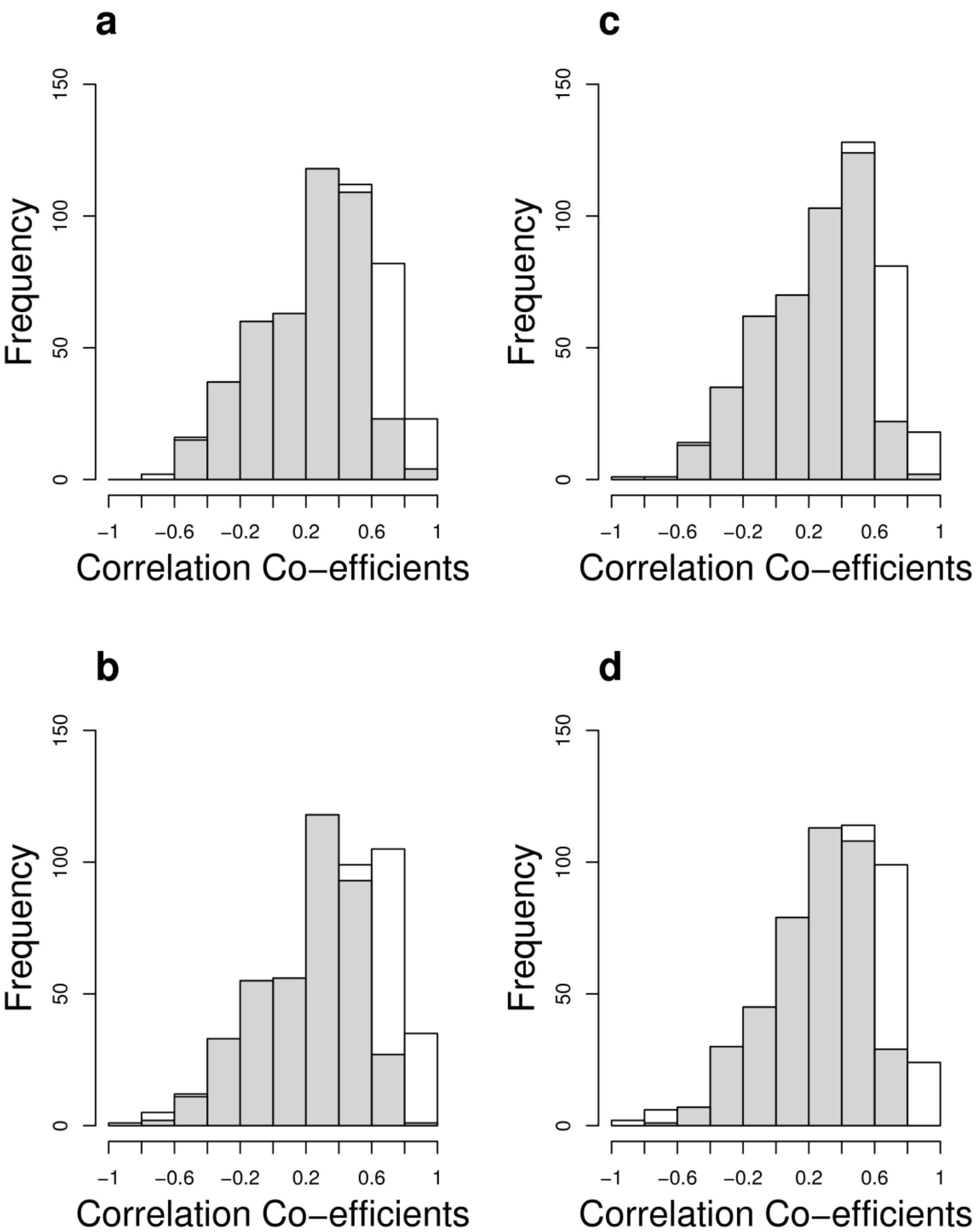

Figure 6.6. Distributions of the correlation coefficients of the correlation maps displayed in Figure 6.5 with the monthly percentage of over- (a, c) and under- (b, d) forecasting of FDR vs monthly variance in FO (a, b) and FFS (c, d). The grey portions of the distribution represent the distributions of the insignificant correlation coefficients ($p \leq 0.05$, grey grid squares from Figure 6.5).

As was observed with the over- and under- prediction of FDR and FA correlations, the majority of locations across the conterminous US display non-significant relationships between the over- and under- prediction of STL with either the monthly variance in FO or FFS (grey squares Figure 6.7). Despite the strong tendency toward positive correlations between the over- or under-prediction of FDR and FA, there is a much greater number of grid squares indicating very strong negative correlations between the over- and under-prediction of the STL and concurrent FA (Figure 6.7). In general negative correlations represent 29.5% of the total significant correlations between over-prediction of STL and FO and FFS, whilst 22.8% account for the under-prediction of STL with FO and FFS. The most negative correlations appear to be found in the Southern California and Southern GACCs for over-prediction (Figure 6.7a, c). Whilst for under-prediction the most negative grid squares appear to be focused in the Western US (Figure 6.7b, d).

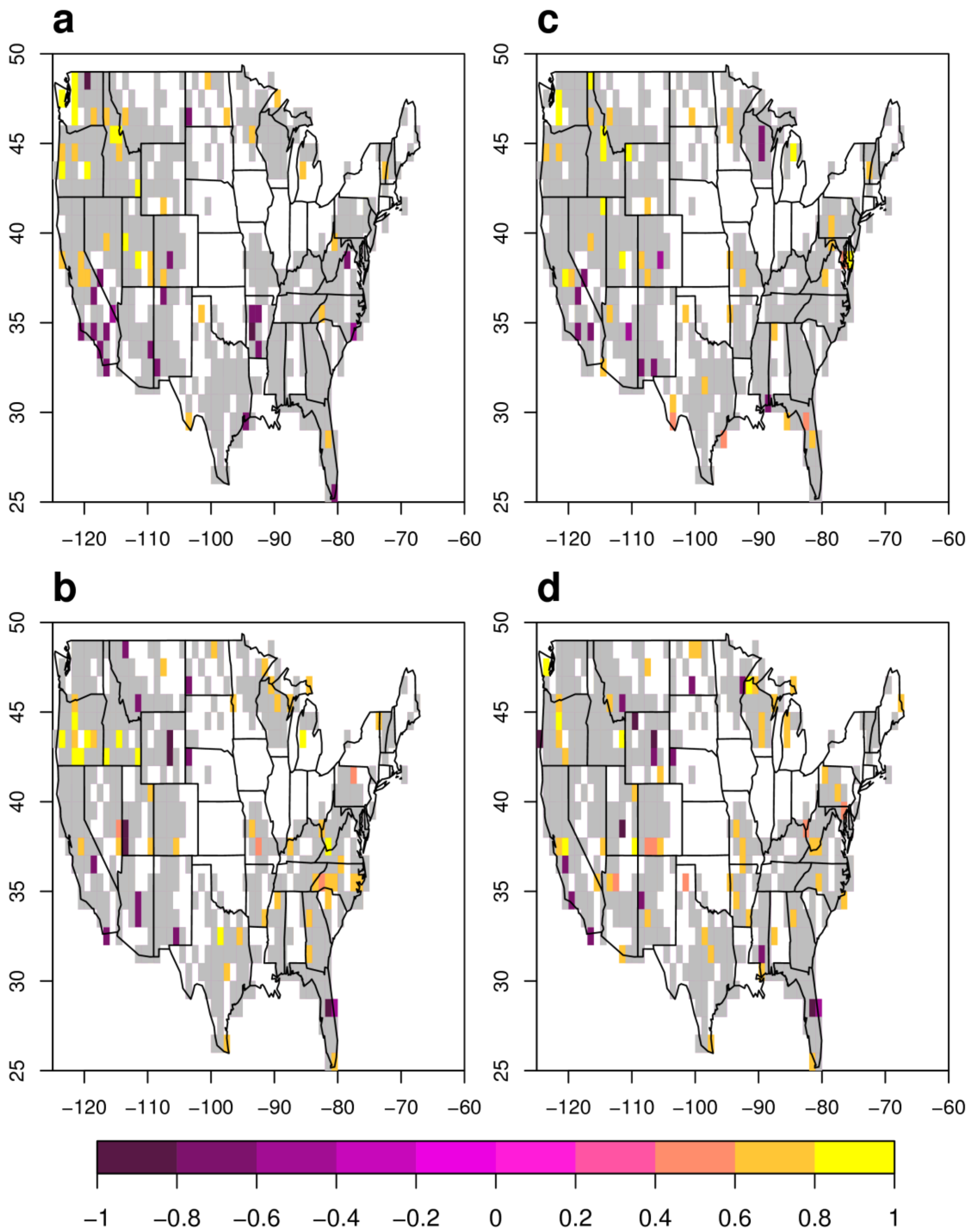

Figure 6.7. Maps of correlation coefficients of monthly percentages of over- (a, c) and under- (b, d) forecasting of STL vs monthly variance in FO (a, b) and FFS (c, d) per grid square across the conterminous US. Insignificant correlations are represented as grey grid squares (p ≤ 0.05).

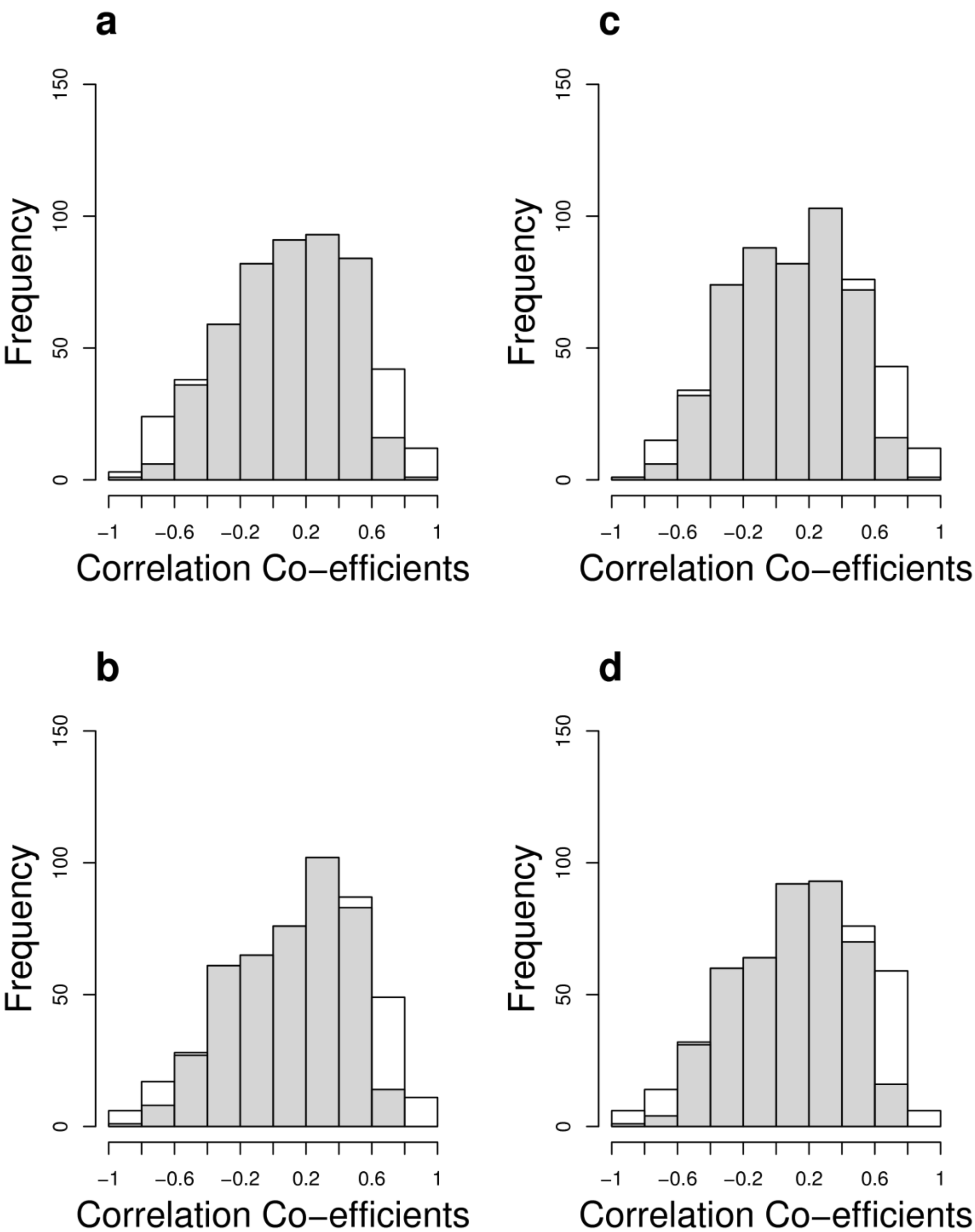

Figure 6.8. Distributions of the correlation coefficients of the correlation maps displayed in Figure 6.7 with the monthly percentage of over- (a, c) and under- (b, d) forecasting of STL vs monthly variance in FO (a, b) and FFS (c, d). The grey portions of the distribution represent the distributions of the insignificant correlation coefficients ($p \leq 0.05$, grey grid squares from Figure 6.7).

As with FDR and STL, the majority of grid squares across the conterminous US display insignificant correlations between the over- and under-prediction of the IC and monthly variance in FA (grey squares Figure 6.9). Similar to the relationship between FDR and FO and FFS, under-and over-prediction of IC with FO and FS can be seen to show strong positive correlations across much of the conterminous US (coloured squares Figure 6.9). Again negative correlations account for fewer than five grid squares of those indicating significant correlations. However, in contrast to the FDR the few negative correlations are more widespread and appear to show little spatial relationship.

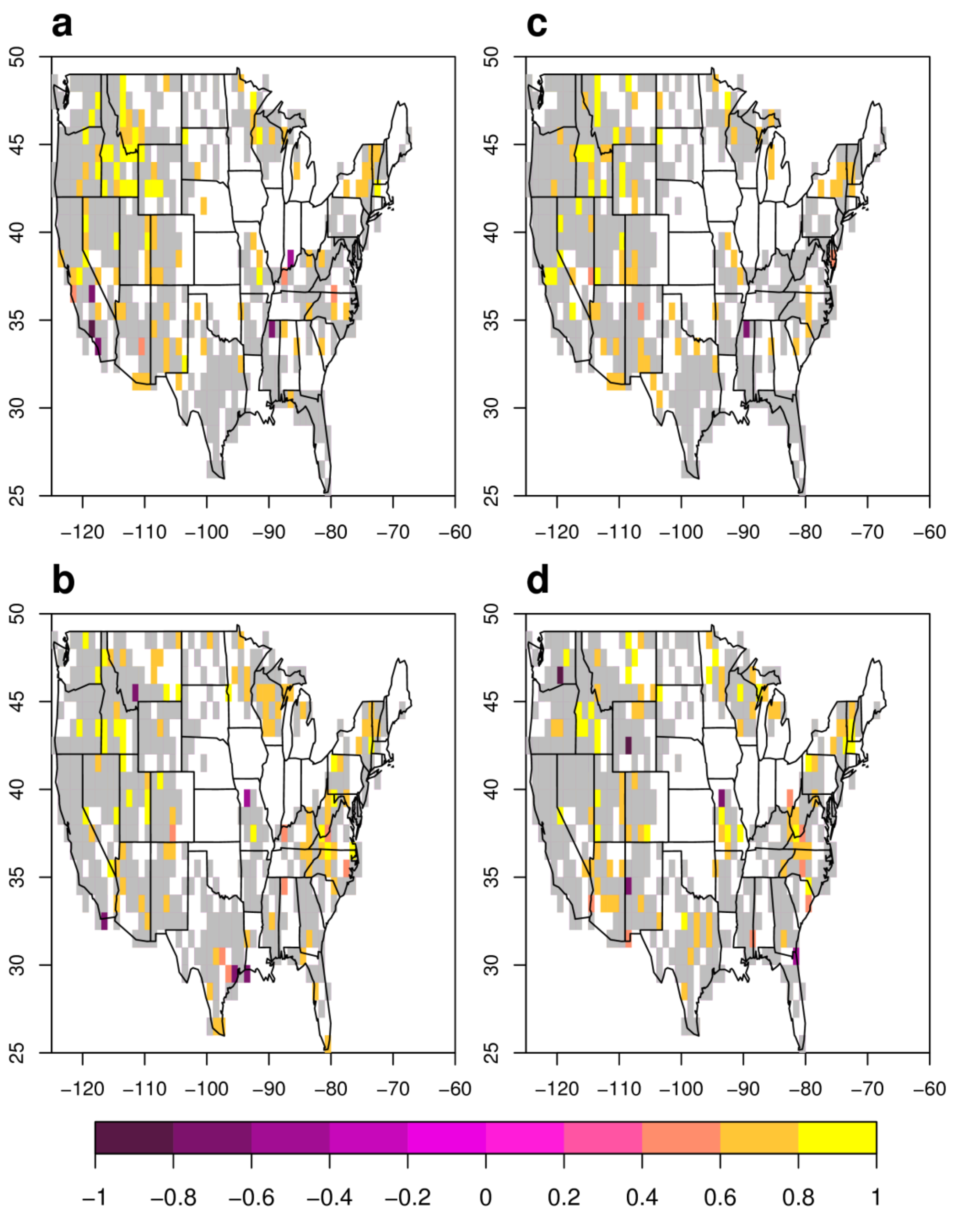

Figure 6.9. Maps of correlation coefficients of monthly percentages of over- (a, c) and under- (b, d) forecasting of IC vs monthly variance in FO (a, b) and FFS (c, d) per grid square across the conterminous US. Insignificant correlations are represented as grey grid squares (p ≤ 0.05).

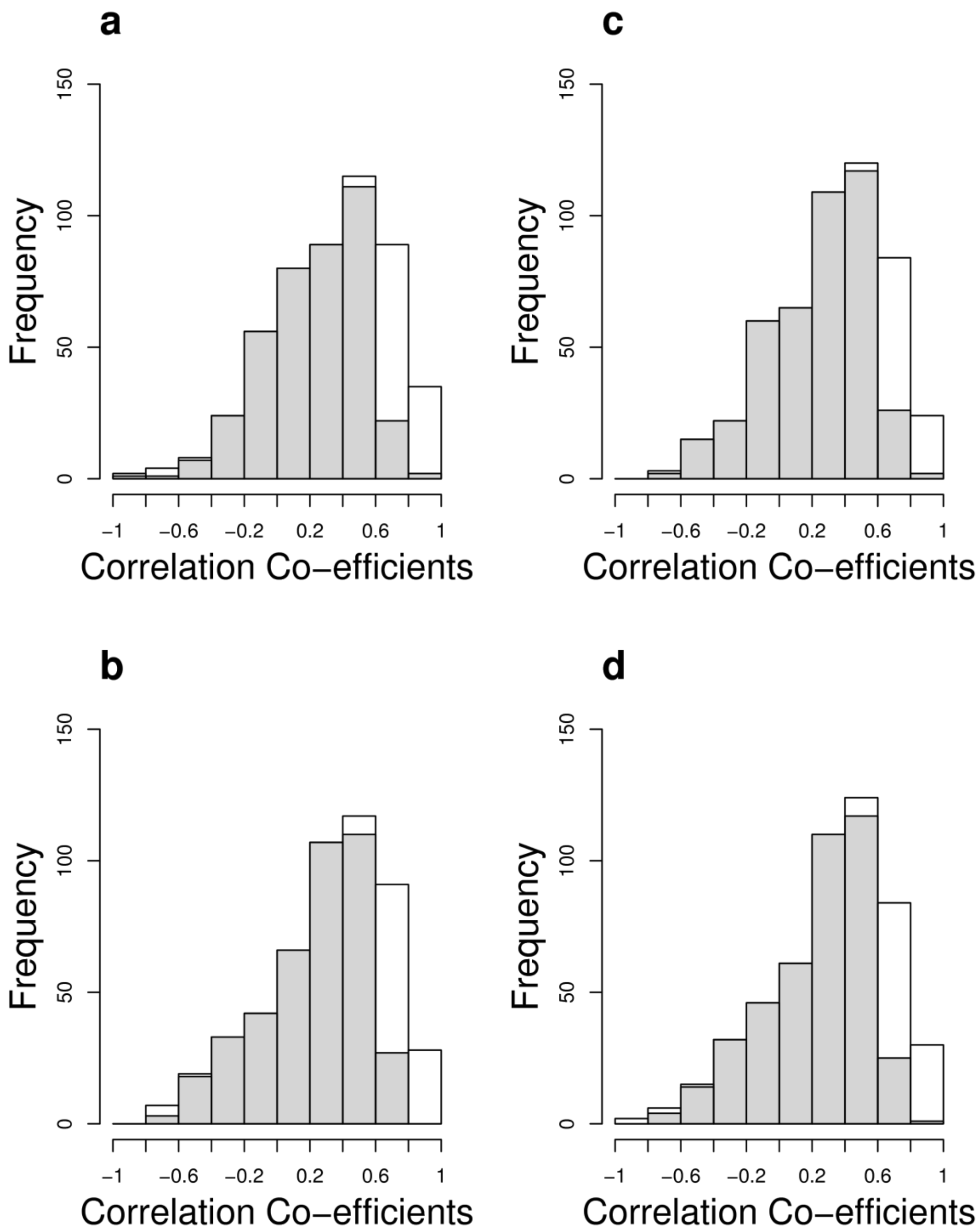

Figure 6.10. Distributions of the correlation coefficients of the correlation maps displayed in Figure 6.9 with the monthly percentage of over- (a, c) and under- (b, d) forecasting of IC vs monthly variance in FO (a, b) and FFS (c, d). The grey portions of the distribution represent the distributions of the insignificant correlation coefficients (p ≤ 0.05, grey grid squares from Figure 6.9).

6.3.4. Temporal and spatial relationships between Forecast Accuracy and Fire Activity

Figure 6.11 takes the aggregated national monthly mean percentages in correct-prediction per FDI (FDR; 6.11a, 6.11d, STL; 6.11b, 6.11e, IC; 6.11c, 6.11f) and explores how this correlates with monthly variance in FA (FO; 6.11a, 6.11b, 6.11c, and FFS; 6.11d, 6.11e, 6.11f). There is a significant strong negative correlation displayed between the accurate forecasting of the FDR and FO ($r = -0.73$, $p \leq 0.05$, $n = 12$, Figure 6.11a), whilst the correlation between the FDR forecast accuracy and FFS is insignificant (Figure 6.11d, $p \leq 0.05$). Moreover the level of accurate forecasting of the STL does not display significant correlations with either monthly variance in FO nor FFS (Figure 6.11b, e, respectively, $p \leq 0.05$). However the level of accurate forecasting of the IC does show significant strong negative correlations with both the monthly variance in FO and FFS ($r = -0.87$, -0.78, $p \leq 0.05$, $n = 12$, respectively, Figure 6.11c, f). Table 6.2 details the correlation coefficients for each correlation pair displayed in Figure 6.11.

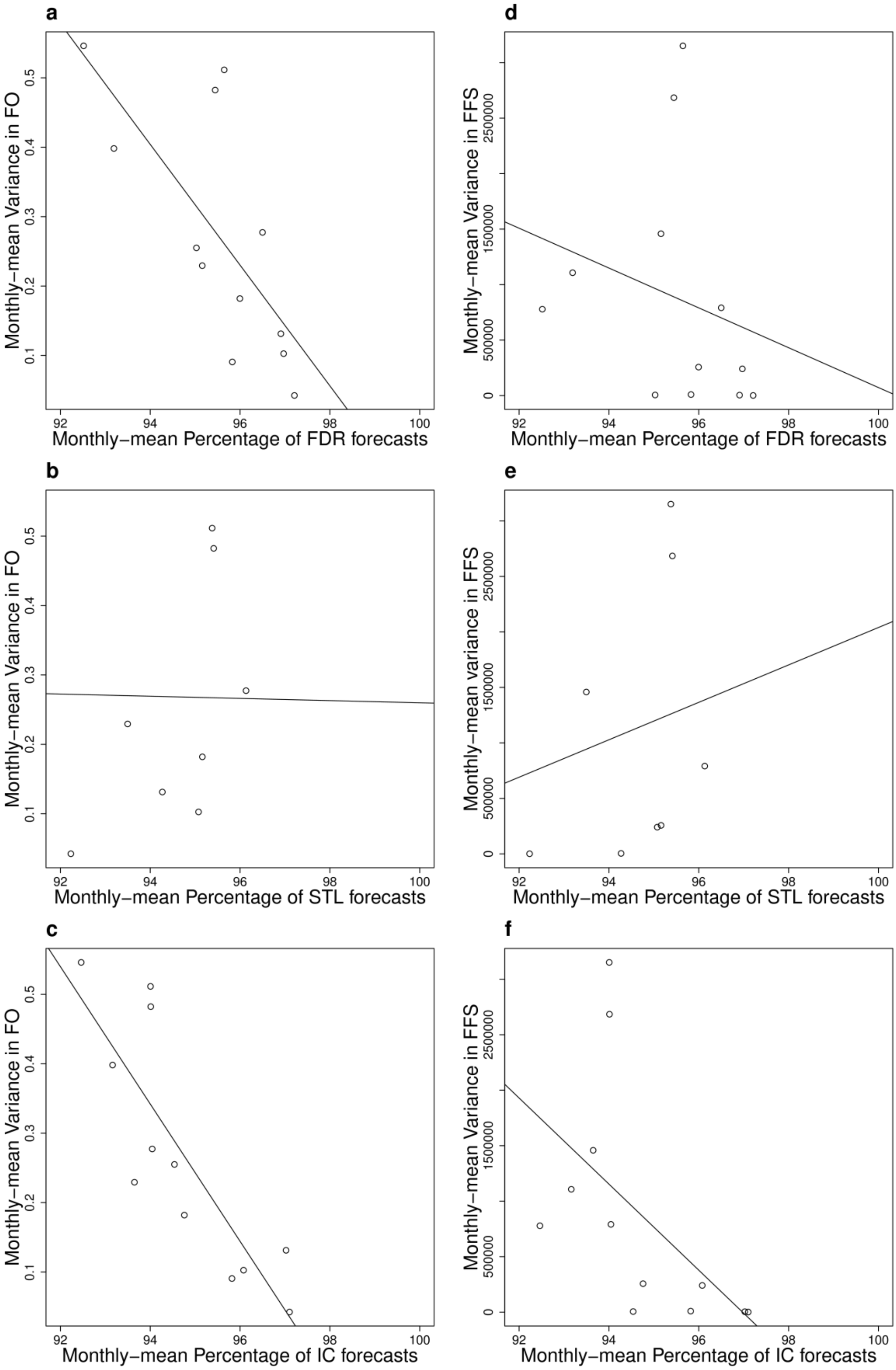

Figure 6.11. Correlations between monthly variance in FO (a, b, c) and FFS (d, e, f), and the monthly percentages of correct-forecasts per FDI (FDR; a, d, STL; b, e, IC; c, f).

Figure 6.12 spatially displays the correlation coefficients of monthly variance in FO and FFS, and monthly mean percentages of correct-prediction per FDI for each grid square across the conterminous US. Figure 6.12 appears to support the results indicated in Figure 6.11 where the correlations between the accurate prediction of the FDR and FO, and the accurate –prediction of IC and, FO and FFS, appear to be dominated by strong negative coefficients, with very few grid squares (< 6) displaying positive relationships between the variables (Figure 6.12a, c, f). Additionally in Figure 6.12, the significant correlations between the accurate-prediction of FDR and monthly variance in FFS also appears to be dominated by strong negative relationships. The accurate-prediction of the STL, however, appears to have different correlations across the conterminous US with FO and FFS (Figure 6.12b, e). The spatial patterns here display a much higher proportion of grid squares where positive relationships between increased forecast accuracy of the STL and fire activity are present (38.8% and 32.7%, FO and FFS, respectively). Moreover, Figure 6.12 mirrors the results presented in Figures 6.5, 6.7, and 6.9, where there are a substantial proportion of grid squares that display insignificant correlations between the level of forecasting accuracy and monthly variance in fire activity for all 3 of the FDIs ($p \leq 0.05$).

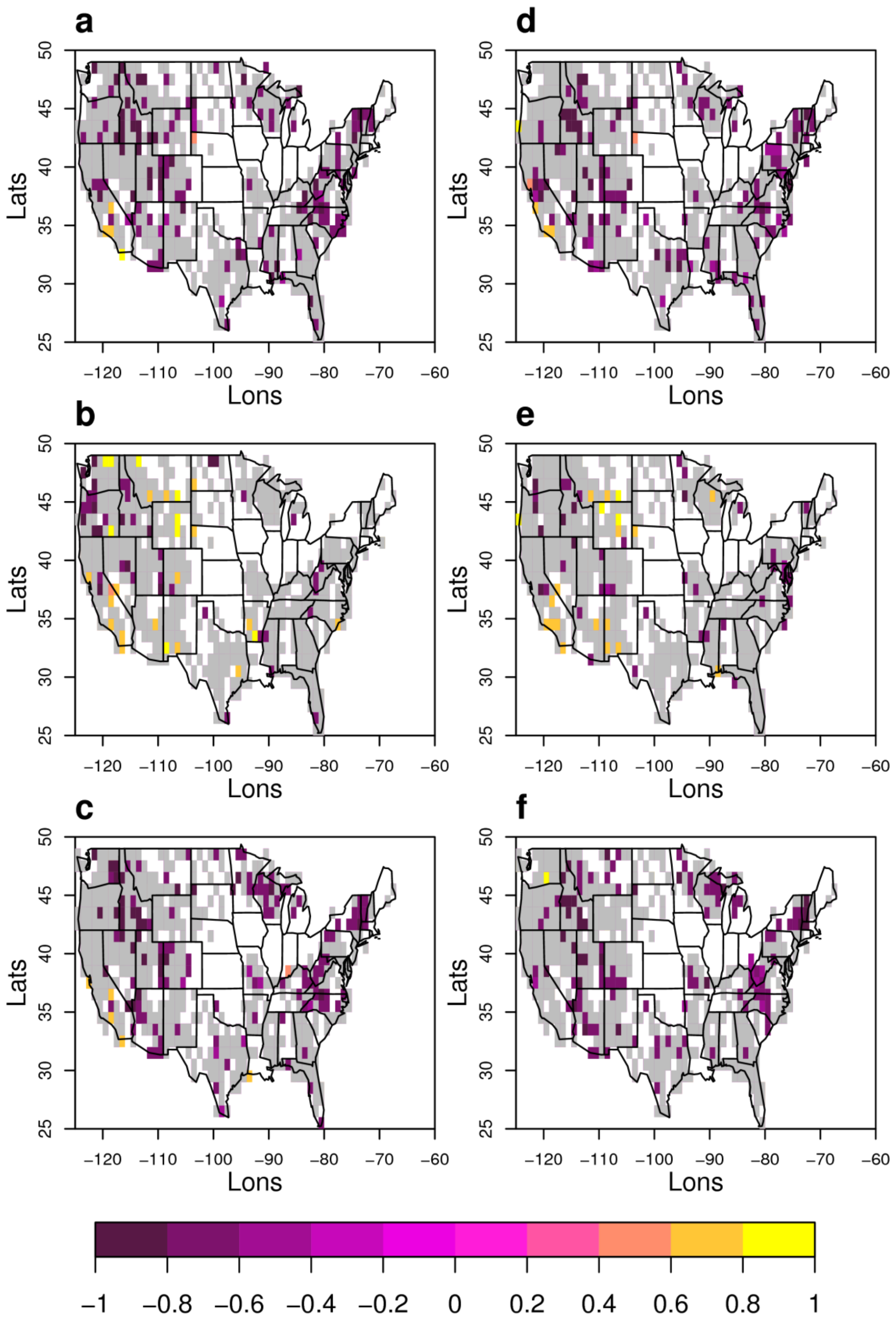

Figure 6.12. Maps of correlation coefficients of monthly percentages of correct forecasting of each FDI (FDR; a, d, STL; b, e, IC; c, f) vs monthly variance in FO (a, b, c) and FFS (d, e, f) per grid square across the conterminous US. Insignificant correlations are represented as grey grid squares (p ≤ 0.05).

6.4. Discussion

The aim of this study was to ascertain whether the accuracy of the 1-day forecasts of the NFDRS impacted and or related to changes in fire activity in the conterminous US. As expected, extremely inaccurate forecasts accounted for approximately 5% of the daily fire danger reports, indicating near-normal distributions of error. Forecasting inaccuracy appears to vary throughout the year, with over-prediction of the FDIs ranging from 1-8%, and the under-prediction of the FDIs ranging between 1-4%. The percentage of daily reports that resulted in either the under-prediction or over-prediction of fire danger can be as much as 35% in some regions of the conterminous US. Moreover there are considerable spatial variations in the distribution of over- and under-prediction for all FDIs across the country with regions in the northwest exhibiting clear regions of inaccurate forecasting (Figure 6.2).

It would be expected that changes in the amount of accurate forecasts of fire danger would impact on the success and provision of suppression activities through the year, and that this should be reflected in trends in fire activity, in either the variability in the occurrence of fires, or in the final sizes of each fire event. When exploring the relationships between the amount of forecasting accuracy/inaccuracy and concurrent wildfire activity, a number of temporal patterns were shown.

All the correlations between levels of accuracy/inaccuracy of IC forecasts and monthly variance in FA (Figure 6.4 and 6.11) are statistically significant ($p \leq 0.05$). From Figure 6.11c, f, as correct forecasting is reduced, there are increases in monthly variance in FO and FFS. Additionally as the over- and under-prediction of IC increases, so too does variance in FO and FFS. The majority of inaccurate forecasts in IC appear to be in the months of March, April, May (MAM), and August. At the same points in the year, peaks in FO variance can also be observed (Figure 6.3). IC forecasts appear to be inaccurate at the time when fires occur more. In MAM and August, more fires occur that require suppression than the forecasted IC indicate. Moreover, when considering the relationships between the forecast accuracy/inaccuracy of IC and monthly variance in FFS, peaks in IC forecasting inaccuracy corresponds to a peak in FFS in the months of July, August, and September (JAS),

However, interestingly a greater period of inaccuracy occurs in April which does not correspond to a peak in variance in FFS. This finding is unexpected as the IC represents the probability of a fire occurring that requires suppression, therefore if this was to be under-predicted, then the resulting observed conditions would be inferred to lead to a greater FFS for that period of time, represented here as increased variability in FFS. Therefore other mechanisms must be considered before further conclusions can be deduced. Considering the forecast accuracy/inaccuracy of the STL, from Figures 6.4 and 6.11 there are no significant relationships between the inaccuracy and accuracy of STL forecasts with the monthly variance in either FO or FFS. The accuracy and inaccuracy of STL forecasts does not correspond to changes in FO and FFS. However, periods of greatest under-prediction in STL (Figure 6.3c) do appear to loosely correspond to peaks in FO to a lesser significance ($p = 0.052$). The STL appears to be most wildly over-predicted through the months of November to April, but not in the summer period. This is at odds with the trend in FO. From

December to April the STL is persistently inaccurate nearly 10% of the time but this is nearly halved during the summer. It seems to be that the forecasts are more ‘correct’ when it counts (during the summer and active fire season), and more inaccurate, with persistent over-prediction, when it might be perceived to matter less (winter months).

From Figure 6.11, accurately forecasting the FDR has a significant relationship with FO, where increasing accuracy corresponds to decreases in variance in FO. However there is less of a clear relationship between the accuracy of FDR forecasts and the corresponding variance in FFS. Moreover there are no significant relationships between the over-prediction of FDR forecasts and either the variance in FO or FFS (Figure 6.4a, d). However the under-prediction of the FDR exhibits significant ($p \leq 0.05$) positive correlations with both monthly variance in FO and FFS. Peaks in under-prediction of the FDR in spring and summer correspond to peaks in variance in FO and FFS through the year whilst peaks in over-prediction of the FDR in spring corresponds to a peak in variance in FO, but there is limited over-prediction in summer where there is a second peak in FO variance.

Reasons why different relationships can be seen between the levels of accuracy and inaccuracy of forecasting across the different FDIs and FA could be due to the types of fire that occur and burn through the year. By breaking down monthly totals of FO and FFS over the study period (2006-2013) by fire cause (as defined by Short, 2014, in FPA FOD), interesting patterns emerge (Figure 6.13 and 6.14). The FPA FOD classify each recorded fire event into one of thirteen categories which encompass a range of causes of fire, both physical and human. The two fire causes that are most apparent in MAM and JAS (Figure 6.13 and 6.14) are ‘Debris Burning’ and ‘Lightning’.

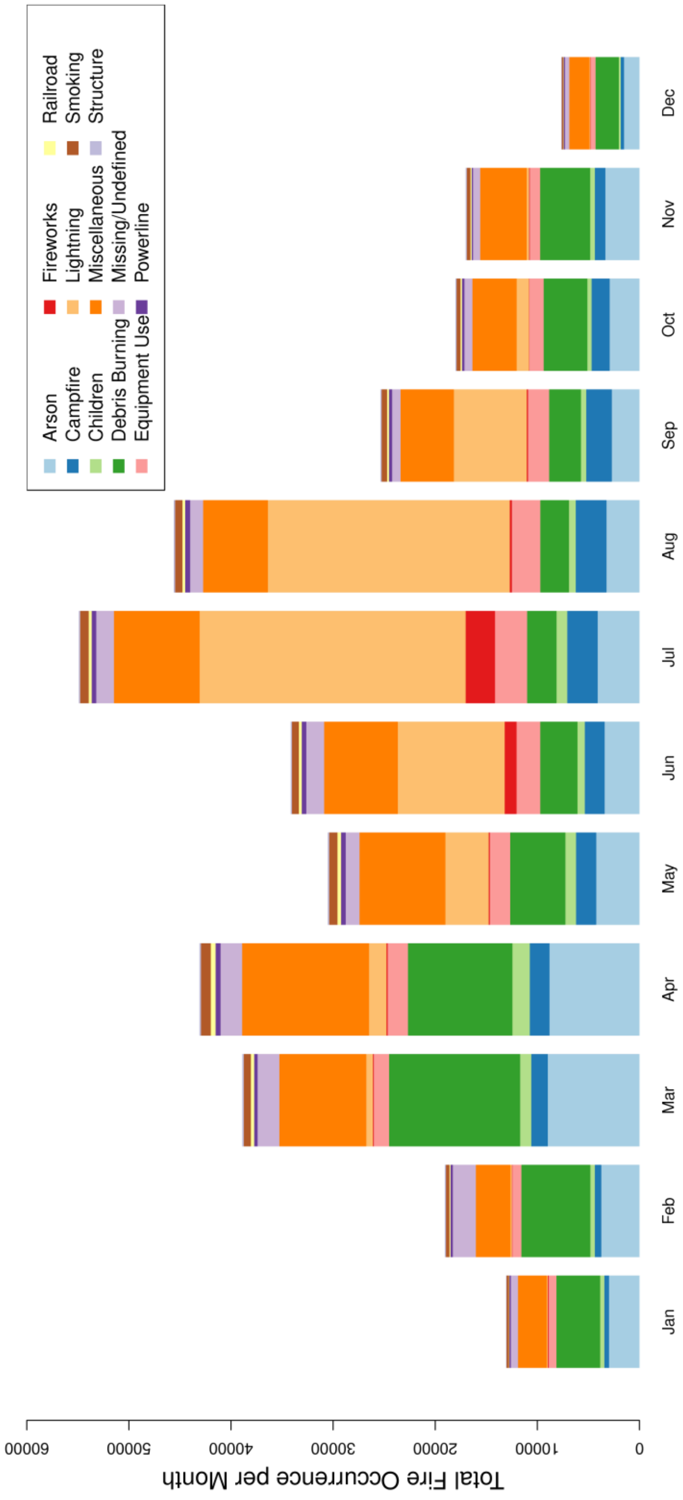

Figure 6.13. Bar plot of Total FO per month from 2006-2013, divided by Fire Cause (defined by Short 2014, FPA FOD).

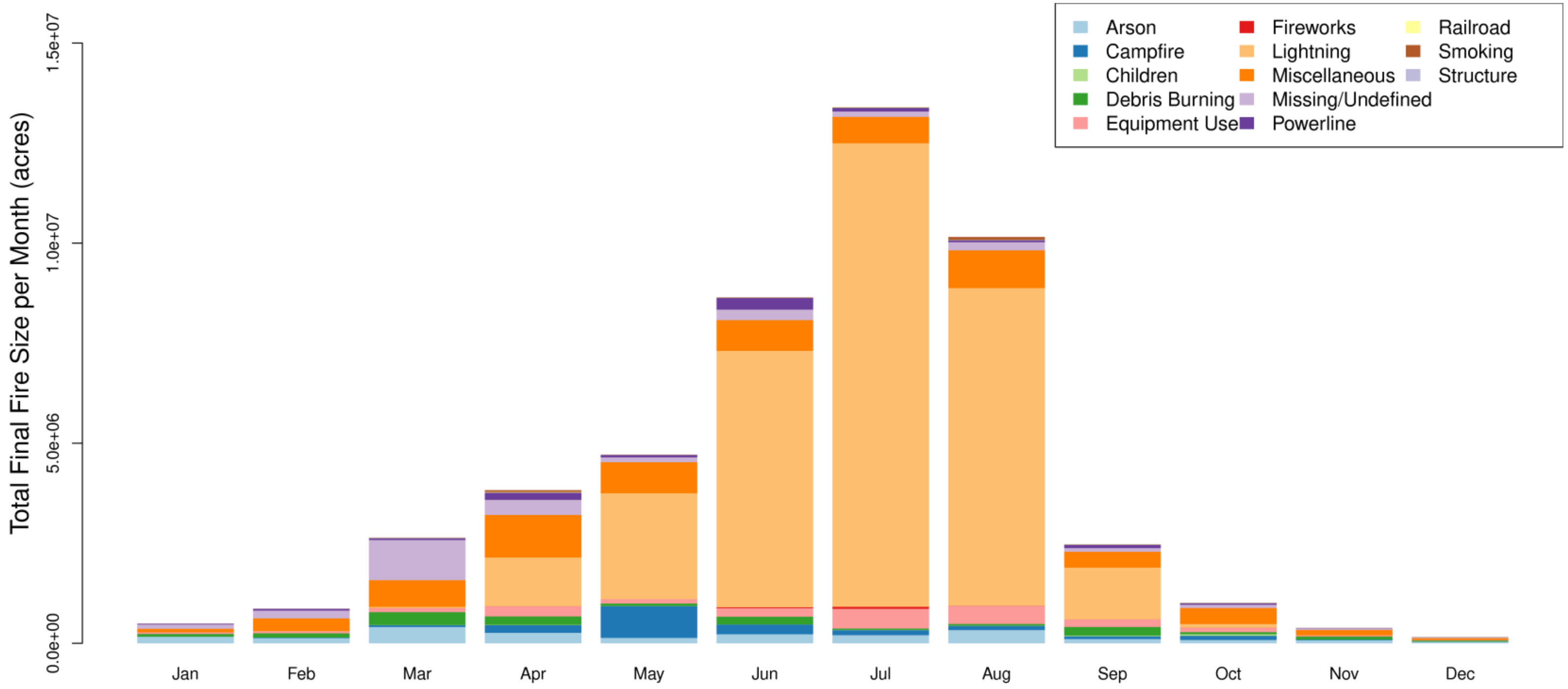

Figure 6.14. Bar plot of Total FFS per month from 2006-2013, divided by Fire Cause (defined by Short 2014, FPA FOD).

In MAM there is a noticeable increase in the number of fire occurrences caused by debris burning, whilst from May to September lightning caused fire occurrences appear to account for the majority of fires. This observation is in line with the findings of Whitman et al. (2015) where ignition causes were strongly linked to seasonality with lightning caused ignitions increasing through the summer and declining into the autumn. The increasing trend in lightning caused fires is synchronous with increasing trends in the proportion of total FFS from April to September (Figure 6.14) which is in accord with the majority of annual burned area in the western US being due to lightning-ignited fires (Westerling et al. 2003, Westerling, 2016, Walding et al 2018 Chapter 4 - Figure 4.5). Lightning induced fires may not be as easily actionable in the summer even though STL and IC forecasts are more accurate during this period. This could be owing to the remoteness of the fire and the type of fuels that are burning, where the presence of finer fuels may lead to lower live fuel moisture and higher resulting spread rates. Moreover, the presence of fine fuels may lead to increases in area burned in a region owing to the fine fuels, such as grasses, being able to regenerate faster than heavier fuels, thus shortening fire return intervals for a given region (Westerling et al. 2003).

The peak in FO due to debris burning however does not correspond to a spike in FFS, indicating that the fires that occur due to debris burning led to smaller escaped fires (Figure 6.12 and 6.13). What is interesting is that these are human-caused fires (debris burning source) and therefore the limited variance in FFS shown in Figure 6.3, may be owing to the fires being easily actionable as they must, by definition, be closer to inhabited areas. And if fires are detected quickly and easily they can often be successfully suppressed by the initial attack (Arienti et al. 2006).

Chapter 4 identified, that the majority of debris burning happens in the Southern and Eastern GACCs (Figure 4.5) and secondly, that the STL has a weaker correlation to FFS in the southeast (Figure 4.3). Coupling this with the findings from this chapter, that the largest proportion of debris burning occurs during March and April, the majority of STL over-prediction may be occurring in the southeast and may be the cause of the FFS and STL being decoupled in this region. Following on from Chapter 4, there are clearly geographical inconsistencies in correlation strength between the FDIs and FA, from the findings presented here seasonal differences are also apparent. Previous recommendations on the NFDRS needing improvement in the southeast (from Chapter 4), now need to be extended to focus on spring months as well.

Based on the theory that correct forecasting of fire danger would facilitate appropriate fire management actions to suppress, control, and contain wildfires, one would expect that if forecasting accuracy were to increase, then fire activity would decrease as the number and size of fires would reduce through effective fire management. The relationships between forecasting accuracy and fire activity for each of the 3 FDIs however do not portray this idea uniformly. As the level of forecast accuracy increases for the FDR and the IC, there are strong negative correlations exhibited with the variance in FO, whilst variance in FFS only appears to decrease with IC forecast accuracy (Figure 6.11a, c, f, $p \leq 0.05$). Whilst the accurate forecasting of the STL displays no significant relationship with neither the FO nor the FFS. In addition to this, the FDR also fails to display a significant relationship with the FFS (Figure 6.11b, d, e, $p \leq 0.05$).

Moreover, the majority of locations across the conterminous US display insignificant relationships between the levels of accurate forecasting of all of the FDIs and fire activity (Figure 6.12). It should be noted however that in locations where there are significant correlations between the forecast accuracy and FA, the vast majority exhibit very strong negative relationships, as theorised, and that this is mainly owing to the FDR and IC. The spatial relationships between the accurate forecasting of the STL and FA do interestingly show some significant positive correlations where increased accuracy of STL corresponds to increases in variance in FO and FFS.

The lack of significant relationships between the level of accuracy and inaccuracy in FDI forecasting and fire activity across the US is surprising based on the proposed theory that accurate forecasting would facilitate successful mitigative actions. However this lack of a signal/ consistent relationship across the conterminous US may be owing to the potential use of NFDRS outputs by fire managers and their reliance on the system. This highlights sentiments expressed by Schlobohm and Brain (2002) where NFDRS outputs are merely one tool in a fire manager's toolbox, where local knowledge and expertise are placed in high regard, with great value and utility. Therefore if a forecast were to be under-predicted in a specific location, then on that local scale the assigned/responsible fire manager may be aware of this due to the time of the year, status of live/dead fuel or any other number of intrinsic/intangible sets of knowledges (such as the Southern and Eastern GACCs) that they possess and rely on that they use instead. Moreover, other forecast tools such as the monthly significant Wildland Fire Potential outlooks (https://www.predictiveservices.nifc.gov/outlooks/outlooks.htm, accessed 18th April 2018), and the NWS Storm Prediction Centre 1-, 2-, and 7-day Fire Weather Outlooks (http://www.spc.noaa.gov/products/fire_wx/fwdy1.html, accessed 18th April 2018) may be utilised by fire managers and could be in disagreement with the NFDRS forecast and so fire managers may choose to focus on and act on these alternatives instead or use all sources of information together to make informed pre-plan decisions.

6.5. Conclusion

This chapter has determined that the 1-day forecasts of fire danger from the NFDRS are ~95% accurate overall. However it has been demonstrated that the level of accurate forecasts fluctuates through the year, with peaks in under-forecasting in MAM and JAS, and high levels of over-prediction in winter and spring months. Regions across the conterminous US, including; Wyoming, Nevada, Montana, and the eastern seaboard have been shown to have a high percentage of daily reports where fire danger has been forecasted incorrectly. Seasonal trends in forecasting (in-) accuracy have been shown to coincide with trends in fire activity, and support findings from previous chapters in this thesis, whilst spatially explicit relationships between forecasting accuracy and fire activity may infer that the NFDRS outputs are not overly relied upon by fire managers.

“He is talented, very talented but he has no brains”

Geoffrey Boycott

Chapter 7: The importance of variable wildfire danger conditions in determining the size of wildfires.

7.1. Introduction

It is well known that wildfires pose significant threats to both the natural environment and human populations (Bowman et al. 2009) and that they are driven by a number of natural factors such as temperature, precipitation, wind, humidity, fuel availability, and the location of lightning strikes (Westerling et al. 2003). Over recent decades fire activity in the USA has increased with the number of large wildfires (Barbero et al. 2014, Dennison et al. 2014), annual burned area (Westerling et al. 2006, Littell et al. 2009) and the duration of the fire season is lengthening (Preisler and Westerling, 2006, Flannigan et al. 2013, Jolly et al. 2015a), all showing striking upward trends since the end of the 20th century. Anthropogenic climate change, increased settlement development at the Wildland-Urban Interface, natural climate variability, and a legacy of historic fire suppression increasing fuel loads, have all been shown to have contributed to the alteration of fire regimes in the USA and the resulting increase in fire activity since the 1980s (Pausas et al. 2004, Schoennagel, Veblen and, Romme, 2004, Westerling et al. 2006, Meyn et al. 2007, Pyne et al. 2008, Littell et al. 2009; Miller et al. 2009, Marlon et al. 2012, Abatzoglou and Williams, 2016, Harvey, 2016).

Of growing concern is the increasing number of large wildfires (LWFs) and very large wildfires (VLFs) (Dennison et al. 2014). VLFs are unprecedented in their influence on property losses, natural resource damage, and account for a disproportional amount of annual suppression expenditure in the USA (Williams, 2013). This has led federal agency suppression expenditure to consistently exceed $1.5billion annually since 2012, with expenditure surpassing $2billion in 2015 and 2017 (National Interagency Fire Center, 2018b). Moreover, US federal agencies have spent approximately $24 billion between 2000 and 2013 on large fire suppression activities (adjusted to 2013 USD) (Calkin et al. 2015). To further emphasise the economic significance of large wildfires, only 1.4% of fires in the USA from 1980-2002 were classed as large wildfires (>300 acres) yet accounted for 94% of the total suppression expenditure by federal agencies (Strategic Issues Panel on Fire Suppression Costs, 2004, Holmes et al. 2008).

The USA has significant expertise, money, and infrastructure invested in the management and suppression of wildland fires. Despite this LWFs still occur and have lasting impacts on both the natural and built environment. Recent events such as the 2017 northern and southern Californian wildfires further signify the impact of LWFs and VLFs. It has been indicated that significant challenges exist over determining the appropriate temporal window over which to associate average fire danger and total burned area (Riley et al. 2013; Barbero et al. 2014a) and that this appears to be because: (1) daily indices lose their ability to capture high-frequency fluctuations when averaged over time (Preisler et al. 2008); and (2) a few high fire spread days (Podur and Wotton, 2011) may account for most of the final fire size (Freeborn et al. 2015). To date existing studies have failed to evaluate the actual NFDRS outputs that were observed at the time of concurrent wildfire activity. The majority of studies have considered relationships between LWFs and NFRDS outputs by utilising fire danger indices that have been reconstructed from climate/weather models (Preisler et al. 2008) rather than the fire danger conditions that were observed and reported during a fire's lifetime. By using the reported data this not only represents the actual fire danger conditions that influenced the fire but also represents the knowledge of fire danger that was acted upon by fire managers and the public. Whereas, recalculated fire danger indices from climate/weather models do not link directly to the reporting stations that aid the management of fires. Here I analyse the observed fire danger data reported by fire managers that occurred concurrently with burning wildland fires. This has been achieved by utilising the NFDRS data archive and the USFS's Fire Program Analysis Fire Occurrence Database (FPA FOD) (Short, 2015a), to create a novel dataset of 12,369 fire events across the conterminous US detailing fire danger conditions, represented by a selection of NFDRS outputs, for every day in over the burn period of individual fires.

Utilising this novel dataset I seek to understand whether fires of different sizes, and especially large wildfires, experience noticeably or significantly different observed fire danger conditions throughout the period over which they burn (e.g. days, months). The rationale behind this is to consider an alternative utilisation for certain NFDRS FDIs in order to predict or pre-empt the development of large wildfires. Even though the NFDRS is not designed to predict the final size of wildfires, I wish to explore whether it can in order to see if there is any information in the NFDRS outputs that can be utilised to predict large wildfires. To achieve this I explore both the magnitude of observed fire danger and the daily variability in observed fire danger conditions through the burning period of individual fires. NFDRS fire danger indices are considered because these are used by fire managers to prioritise suppression activities and resources, and therefore should act as strong determinants of action and decision making on fire activity across the USA. Moreover, the variability in fire danger conditions is considered as a predictor of large wildfires because of the inherent difficulty of forecasting variable/fluctuating fire danger conditions (Chapter 6) and how this may impair fire management actions. Firstly I test the hypothesis that the length of burning duration (BD) is a determinant of fire size. Secondly I consider which outputs from the NFDRS have the strongest relationship with fire size. Thirdly I assess how variability in these outputs varies between different Fire Size Classes (FSCs).

7.2. Methods

7.2.1. Dataset formation

To create the dataset of 12,369 fires I brought together fire activity records from the USFS's Fire Program Analysis Fire Occurrence Database (Short, 2015a) and NFDRS published and publically available Fire Weather Observation datasheets from the Wildland Fire Assessment System (WFAS) data archive (WFAS, 2018d) for the time period 2006-2013, for the whole of the conterminous USA.

The USFS's FPA FOD is a database of fire events that aims to bring together and standardise US federal, state, and local wildfire reports from 1992-2013 into one set of data that can be utilised for statistical analyses of wildfire activity. Details of its construction can be reviewed in Short, (2014). Previous work (Short, 2015b) also highlights that the database may be incomplete in some aspects and in some regions, but stresses that it still facilitates high resolution spatial analysis of wildfire activity across the USA. For the purposes of this study, location data (longitude and latitude), dates of discovery (DOD, the day on which the fire was discovered) and dates of containment (DOC, the day on which the fire was 100% contained), Final Fire Size (FFS, acres), and the Fire Size Class (FSC) data fields were obtained from the FPA FOD for every fire event from 2006-2013. The FSCs are defined by the thresholds described by the National Wildfire Coordinating Group and range in size from 0-0.25 acres for FSC A, and over 5000 acres for FSC G (See Table 7.1 for full definitions of the seven FSCs taken from, National Wildfire Coordinating Group, 2018, https://www.nwcg.gov/glossary/a-z, last accessed 23rd April 2018).

Table 7.1. Table of the different Fire Size Class (FSC) definitions, as described by the National Wildfire Coordinating Group (2018, https://www.nwcg.gov/glossary/a-z, accessed 23rd April 2018) and the number of fires per Fire Size Class in the dataset of 12369 fires used in this analysis.

Fire Size Class	**Size Limits (acres)**	**Number of fires**
Class A	Size ≤ 0.25	5920
Class B	0.25 < Size < 10	4012
Class C	10 ≤ Size < 100	1283
Class D	100 ≤ Size < 300	387
Class E	300 ≤ Size < 1000	306
Class F	1000 ≤ Size < 5000	296
Class G	Size > 5000	165

The NFDRS utilises local weather station input data in order to calculate fire danger indices that describe the worst case burning conditions for a given location and surrounding area (Cohen and Deeming, 1985). Using different combinations of input data such as temperature, precipitation, fuel type, and slope angle, these indices describe different aspects of fire behaviour in terms of likelihood of ignition, potential heat release, rate of spread, and difficulty of control (Deeming et al. 1972, 1977, and outlined in Chapter 2). Through the WFAS data archive (WFAS, 2018d) daily observed NFDRS output data sheets from 2006-2013 were obtained and downloaded. Each data sheet contains weather observations, derived secondary outputs, computed fire danger indices, and a final fire danger adjective rating for each of the reporting weather stations. In this study I use the reported weather station data and fire danger indices observations rather than reconstructed fire danger indices from climate models. This approach does lead to 'gaps' in the spatial distribution of fire danger indices data, resulting in a limited number of fires in the final dataset with daily fire danger data owing to this, however this is a more appropriate representation of the fire danger conditions and the conditions of ‘knowledge’ under which fire suppression actions were taken. For the purpose of this study all observed Fire Danger Indices (FDIs; the FDR, STL, IC, SC, BI, and ERC) produced by the NFDRS are examined. As this analysis intends to highlight which of the indices from the NFDRS best link to determining the size of wildfires, and in particular the FDI conditions that lead to large wildfires, all six were chosen as appose to the more management focus indices examined in previous chapters. Table 7.2 details their definitions and what aspects of fire behaviour they represent.

Table 7.2. Table of the exploratory variables used in this study with their definitions and abbreviations. Sources: Schlobohm and Brain, (2002); and National Wildfire Coordinating Group (2011b).

Term	**Abbreviation**	**Definition**
Fire Danger Rating	FDR	These describe conditions that reflect the potential, over large areas, for a fire to ignite, spread and require suppression.
Burning Index	BI	A number related to the contribution of fire behaviour to the effort of containing a fire.
Spread Component	SC	A rating of the forward rate of spread of a headfire.
Energy Release Component	ERC	A number related to the available energy per unit area within the flaming front at the head of a fire.
Staffing Level	STL	The basis for decision support for daily staffing of initial attack resources and other activities; a level of readiness and an indicator of daily preparedness
Ignition Component	IC	A rating of the probability that a firebrand will cause a fire requiring suppression action.
Fire Danger Indices	FDI	The collective term utilised in this study to refer to the selected NFDRS indices and components used in this study.
Average daily FDI per fire event	FE_[FDI]_mean	The term used in this study to describe the average FDI value per fire event. Calculated from daily FDI outputs present during each fire event's burning period.
Standard deviation of daily FDI per fire event	FE_[FDI]_SD	The term used in this study to describe the standard deviation in FDI values per fire event. Calculated from daily FDI outputs present during each fire event's burning period.
Burn Duration	BD	Length of time (in days) that each fire burns for. Calculated from the Date of Discovery – Date of Containment (DOC-DOD).

In order to couple individual fire events with concurrent fire danger conditions for a given location, latitude and longitude data from both the reporting NFDRS weather stations and the fire event were compared across a 1 x1° degree grid of the conterminous USA. For each grid square, fire danger records and any fire events occurring within the grid square (where multiple fires can occur within the same grid square) were extracted from their respective datasets. Using dates of discovery and containment (referred to as DOD and DOC, respectively), concurrent fire danger records were associated with every fire present in each grid square across the study time period. For every day that a fire burned for (represented here as DOC - DOD) daily mean observed Fire Danger Indices were calculated from observed FDI data from all reporting weather stations present in each grid square. The number of days each fire burned was also calculated (DOC-DOD +1) to represent the burning duration (BD) for each fire event. For each fire, therefore, the observed FDI conditions for each day the fire was burning, and the number of days that each fire burned for were known. The mean observed fire danger conditions for each of the 12,369 fire events using the concurrent daily observed FDI values and one standard deviation (SD) of these daily conditions were calculated. These two summary statistics of the observed fire danger conditions were chosen as measures for the average observed fire danger conditions during which each fire burned, whilst also representing how variable the observed fire danger conditions were during the period of burning.

For every reported fire event I have extracted the mean and SD of each observed FDI output from the NFDRS (FDR, STL, IC, SC, BI, ERC, see Table 7.2 for details), to serve as representative of the overall observed fire danger conditions present whilst each individual fire was burning. For the remainder of this study, I refer to these summary stats for each fire event's (FE) fire danger conditions as FE_[FDI]_mean and FE_[FDI]_SD, respectively (with each FDI listed in Table 7.2 represented, e.g. FE_FDR_mean and FE_FDR_SD). Figure 7.1 shows each fire event present in our dataset in chronological order from 2006-2013. Each line represents the length of time each fire burned for, whilst the colours relate to the seven FSCs (A-G). From Figure 7.1, clear fire seasons can be seen with the majority of fires occurring from May to September for each year. However it can also be noted that fires of all sizes occur throughout the year and burn for a range of durations. This study ultimately seeks to explain the patterns seen in Figure 7.1 with the use of observed fire danger conditions that were present during each fires burn.

The dataset variables were then normalised by range (where, normalised value = (value to be normalised – minimum value in the dataset) / (maximum value in the dataset – minimum value in the dataset), per set of variables to place each set of variables on a scale of 0 to 1) and subgroups of the dataset were also created for each of the seven FSCs, and the exploratory variables (BD, FE_FDI_mean and FE_FDI_SD) were then normalised again within each separate FSC population.

Table A7.1 in Appendix VII provides further details on the data utilised in this chapter with details on how the data was processed and summarised with clearly stating the variables created in the process for use in the analysis.

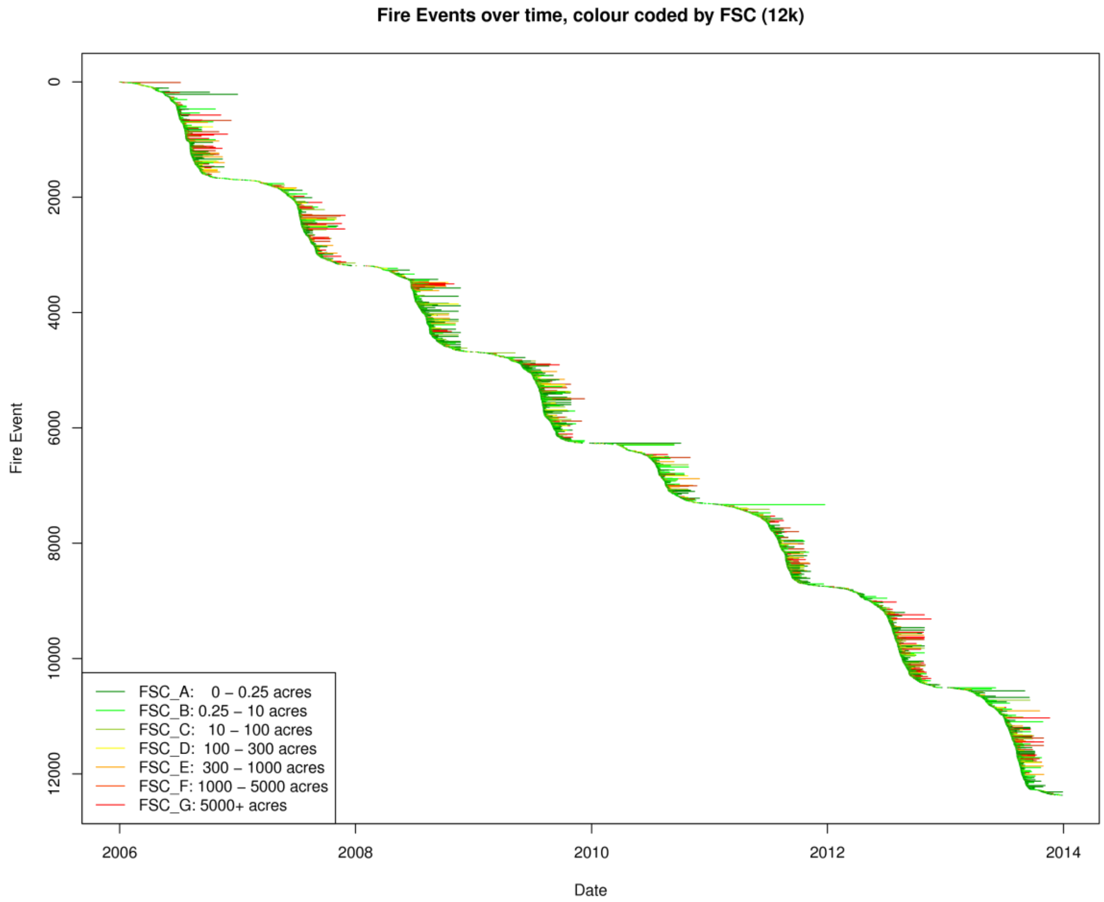

Figure 7.1. Fire events in this dataset in chronological order with the lines representing the length of time each fire burned for (Burn Duration, BD) and the colours corresponding to the seven Fire Size Classes (FSCs).

7.2.2. Data analysis

From the overall dataset of 12,369 fires an initial analysis of the distributions of FDIs (mean and SD) across each of the FSCs was conducted in order to understand how the different FDIs from the NFDRS related to fires of different sizes. I looked to identify variables that showed trends with either increasing or decreasing fire size. Following this, a set of Principal Component Analyses (PCAs) were conducted with a refined number of exploratory variables for each individual FSCs (A-G) separately. This set of focussed PCAs aimed to explore the relative importance of certain variables in explaining the populations' variance within each FSC to enable the comparison of their importance across the FSC spectrum.

7.2.2.1. *Exploratory variable distribution analysis*

Initially, 13 exploratory variables associated with each fire event including the mean and standard deviations (SD) of each FDI (listed in Table 7.2), representing the observed fire danger conditions throughout each fire, and the burn duration of each fire were explored. Percentile boxplots were produced for each FSC per observed FDI variable (FE_FDI_mean and FE_FDI_SD) and BD, to understand how the distribution of the exploratory variables differed between the FSCs. Additionally, the means of the exploratory variables distributions were also plotted (± 1 standard deviation).

Wilcoxon significant difference tests were performed between each of the seven FSCs in order to confirm whether the distributions of each variable were significantly different from one another and enable the comparison of the distributions of exploratory variables for each FSC. Finally, 2-sample Kolmogorov–Smirnov tests were conducted between each of the 7 FSCs to see whether the cumulative distributions of each exploratory variable were significantly different, and how substantial the differences between each distribution were.

From this initial analysis of the 13 exploratory variables, I identified which variables exhibited trends across the FSCs, whether it be the FDI distributions skewing to higher values as the FSC increased or, a greater range of FDI values being present within the FSCs. Variables that showed no significant difference between the different FSCs nor variability between FSCs were not utilised in the next stage of analysis.

7.2.2.2. Fire Size Class PCAs

In light of the first set of analyses, the remaining exploratory variables that appeared to show increasing trends with fire size were analysed for each of the FSC sub groups individually (once normalised relative to their populations) in order to see which variables explained most of the variance within each of the FSCs through a set of PCAs.

From this, bi-plots were produced, and Principal Component (PC) loadings compared, allowing the identification of the different variables that hold significance in the formation of fires within a certain size category. Initially, these individual PCAs were conducted with BD to see how the influence of the duration of a fire's lifespan changes across the FSC spectrum. Once this was conducted the PCAs were then repeated with BD omitted as an exploratory variable in order to see the influence of the other remaining exploratory variables more clearly relative to one another, independent of a temporal dimension.

Table A7.2 in Appendix VII provides further details on the different steps of the analysis in this chapter with explicit descriptions of the variables used, with details on the statistical techniques used, their definition, their justifications for use, and information on how to interpret the specific outputs from each step of the analysis.

7.3. Results

7.3.1. Exploratory variable distribution analysis

The distributions of BD (Figure 7.2a) can be seen to have increasing median values across the seven FSCs with FSC G having the highest median value, and the highest percentile range exhibited. The range of BD values within each FSC also appears to increase, especially when the fire events fall into FSCs of size greater than 300 acres (FSCs E, F, and G). Moreover the mean of BD for each FSC (Figure 7.2b) can also be seen to increase in value across the 7 FSCs with FSC G once again exhibiting the highest value.

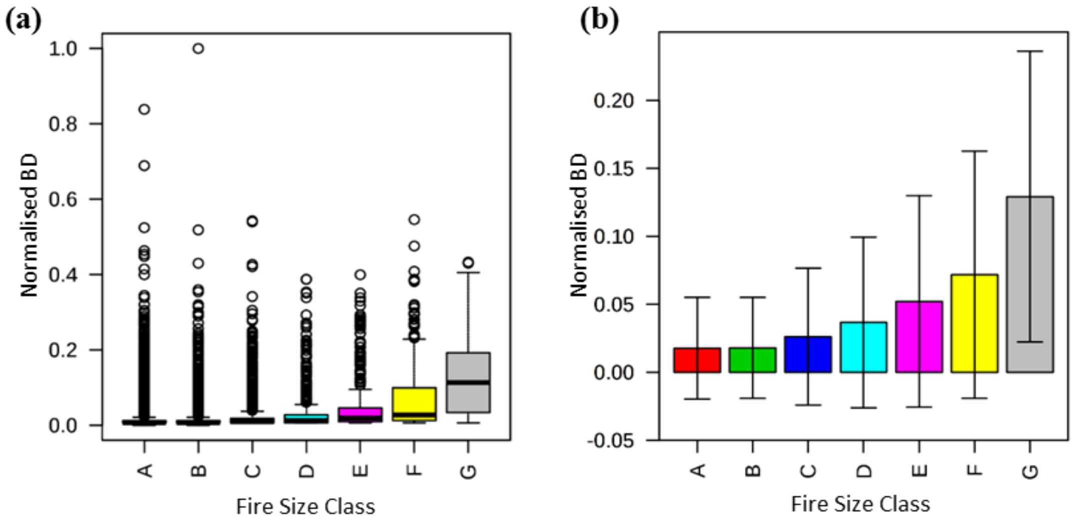

Figure 7.2. (a) Percentile boxplots of normalised Burn Duration (BD), and (b) mean (±1SD) of the distribution of normalised Burn Duration for the 7 Fire Size Classes (A-G).

Exploring the distributions of mean FDIs across the seven FSCs, Figure 7.3 shows percentile boxplots of the normalised mean FDIs for each fire event in each of the FSCs (FE_FDR_mean, FE_STL_mean, FE_IC_mean, FE_ERC_mean, FE_BI_mean, and FE_SC_mean). For all the FDIs, the distributions of values can be seen to overlap considerably across the seven FSCs, with similar median and interquartile ranges. In addition to this, Figure 7.4 shows the means (±1SD) of each of the distribution of mean FDIs displayed in Figure 7.3. The mean values of the FDIs per FSC do appear to show a slight upward trend with FSC, whilst the SDs of each of the distributions appear to overlap across the FSCs.

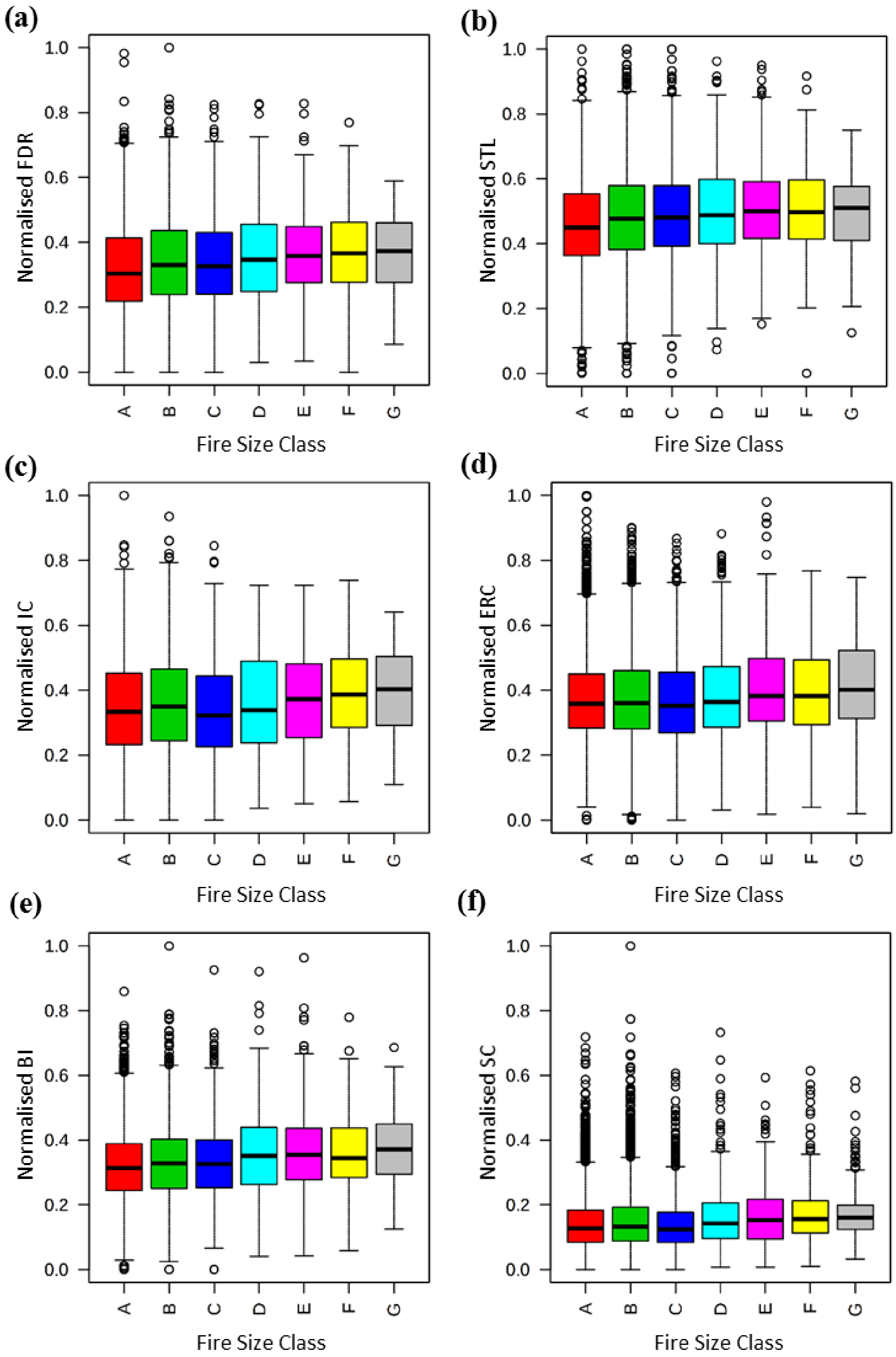

Figure 7.3. Percentile box plots of the mean FDI per fire event (FE_FDI_Mean) for each Fire Size Class (A-G), per FDI; (a) FDR, (b) STL, (c) IC, (d) ERC, (e) BI, (f) SC.

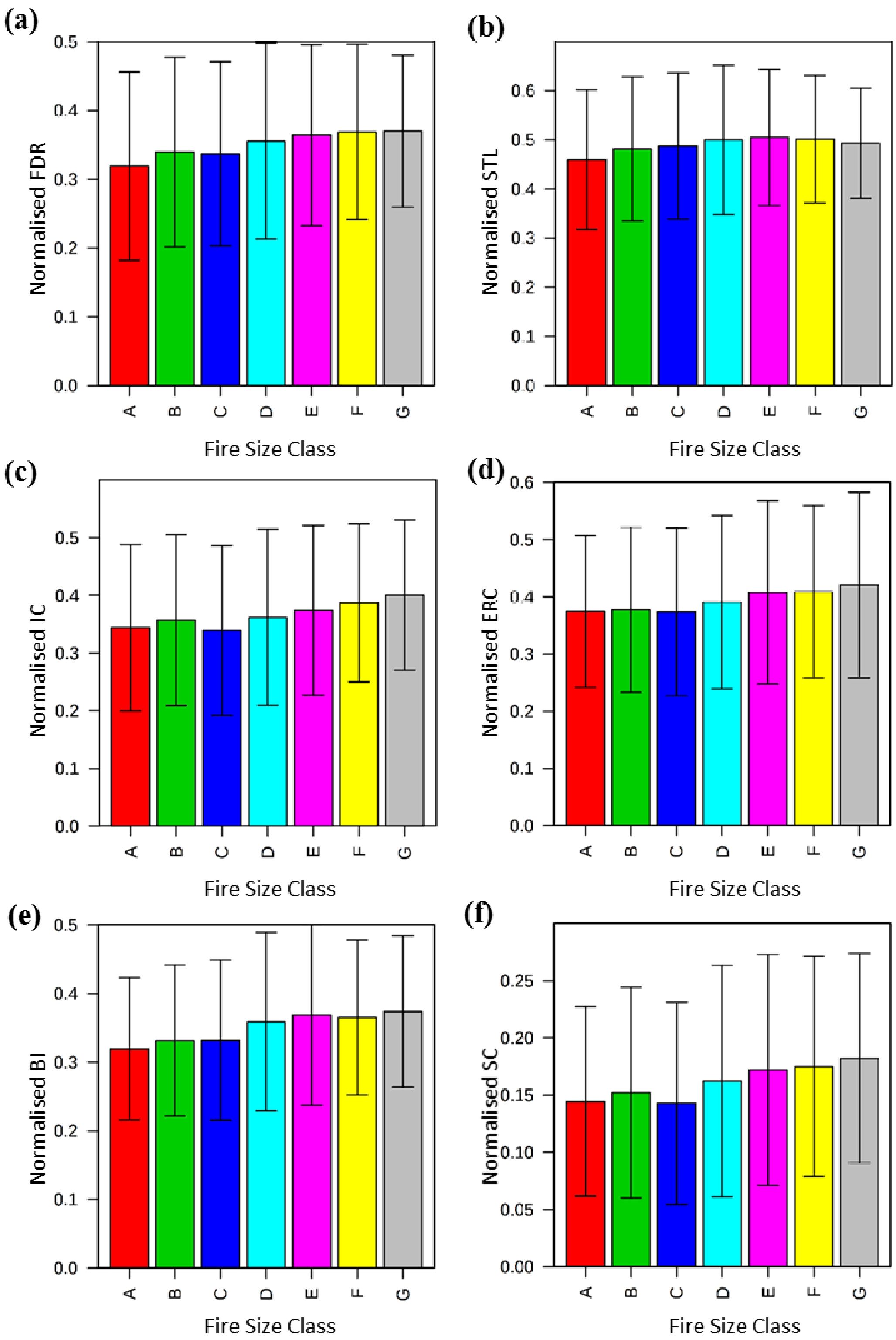

Figure 7.4. Mean (±1SD) values of the distribution of the mean FDI (FE_FDI_mean) for each Fire Size Class (A-G) per FDI; (a) FDR, (b) STL, (c) IC, (d) ERC, (e) BI, (f) SC.

Moving on to explore how the variability in fire danger conditions vary across the 7 FSCs, Figure 7.5 shows percentile boxplots of the normalised standard deviation in each of the FDIs FE_FDI_SD for each of the FDIs in Table 7.2. FE_IC_SD and FE_ERC_SD (Figure 7.5c and 7.5d, respectively) appear to vary more across and within the fire size classes with larger inter-quartile ranges and higher median values than FE_SC_SD and FE_BI_SD (Figure 7.5e and 7.5f, respectively). There is a tendency towards increased FE_IC_SD and FE_ERC_SD over the lifetime of individual fires with the fire events in the largest FSCs having the highest median FE_SD in IC and ERC. Moreover the FE_FDR_SD and FE_STL_SD distributions (Figure 7.5a and 7.5b, respectively) indicate that the Staffing Levels and FDRs are much more variable for larger FSCs than for smaller FSCs, although this is less pronounced than for the IC and ERC (Figure 7.5c and 7.5d, respectively).

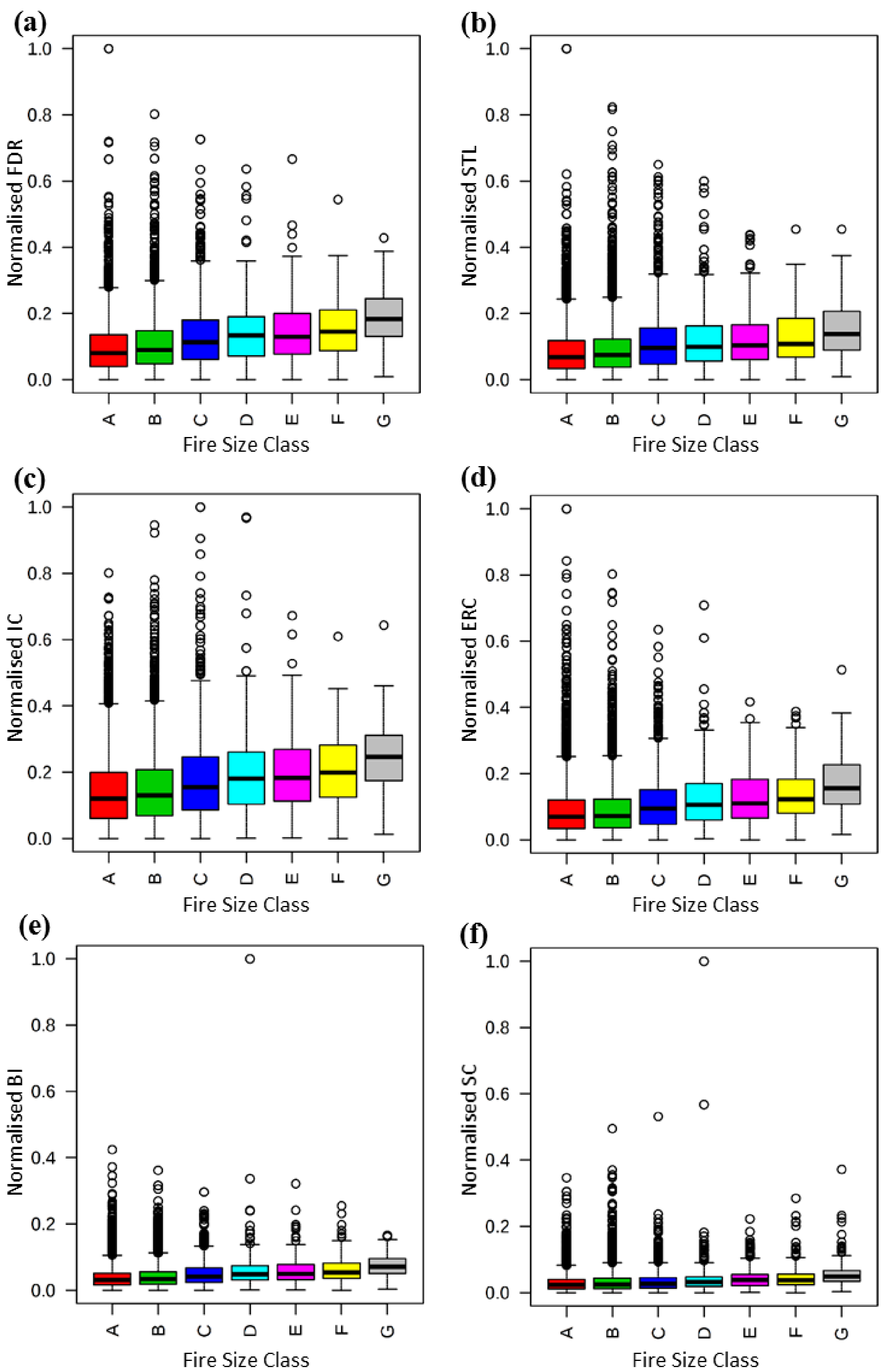

Figure 7.5. Percentile box plots of the standard deviation of the FDI per fire event (FE_FDI_SD) for each Fire Size Class (A-G), per FDI; (a) FDR, (b) STL, (c) IC, (d) ERC, (e) BI, (f) SC.

In addition to this, Figure 7.6 shows the means (±1SD) of each of the distributions displayed in Figure 7.5. All of the panels in Figure 7.6 show increasing mean values for each of the displayed exploratory variables, with the largest fire size class containing the highest FE_FDI_SD for each of the NFDRS outputs implying that greater variability in fire danger conditions may be intrinsic to larger fires. Contrary to this however, from the initial distribution analyses, the majority of the FE_FDI_mean distributions (e.g. the mean daily FDI for each fire event, Figures 7.3 and 7.4) were found to have a greater number of non-significantly different distributions of FDI values across the seven FSC, especially when comparing the higher fire size classes (FSC D-G) (Table 7.3). Moreover, from Table 7.3 it can be seen that the distributions of all FDI variables (FE_FDI_mean and FE_FDI_SD) between FSC D and FSC E, were found to be non-significantly different. The same can be seen when comparing the distributions of FDI variables between FSC E and F as well. These results indicate the complexity and difficulty in distinguishing between small, large, and very large wildfires, and the transitions between their corresponding size classes when exploring the concurrent fire danger conditions. The fire events within each of these FSCs (D, E, and F) appear to experience similar fire danger conditions in terms of the average daily condition whilst the fire is burning, and the variability of the concurrent fire danger conditions as well. The majority of FDI distributions are significantly different when considering the difference between the small and large FSC (based on the 300 acre division) and so does indicate that at least the fire danger conditions experienced at the opposite ends of the FSC spectrum are significantly different. Further to this, Kolmogorov Smirnov tests were conducted to compare the cumulative distributions of the exploratory variables across the seven FSCs and showed similar outcomes to that of the Wilcoxon significant difference tests in Table 7.3 (KS test data not shown).

Based on the lines of enquiry and initial findings described above, the following variables were retained for further analysis; BD, FE_FDR_SD, FE_STL_SD, FE_IC_SD and FE_ERC_SD, based on their significantly different distributions across the FSCs and their marked trends across the seven FSCs.

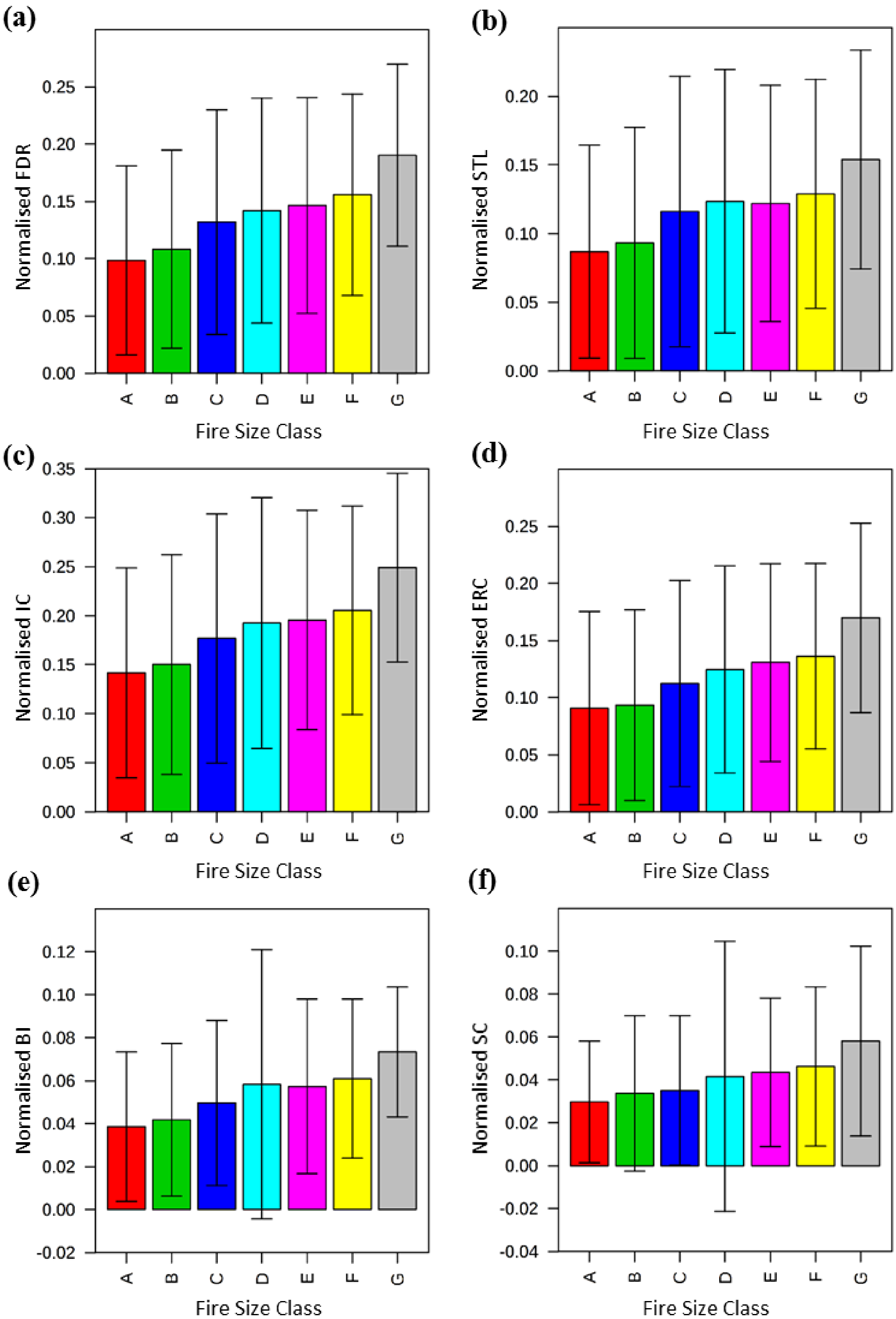

Figure 7.6. Mean (±1SD) values of the distribution of the standard deviation of the FDI (FE_FDI_SD) for each Fire Size Class (A-G) per FDI; (a) FDR, (b) STL, (c) IC, (d) ERC, (e) BI, (f) SC.

Wilcox Tests														
Test Pair	Burn Duration	FE_FDR_mean	FE_FDR_SD	FE_STL_mean	FE_STL_SD	FE_IC_mean	FE_IC_SD	FE_SC_mean	FE_SC_SD	FE_BI_mean	FE_BI_SD	FE_ERC_mean	FE_ERC_SD
A vs B	2.88E-08	5.07E-14	2.25E-10	3.18E-14	0.000314002	2.00E-05	4.73E-05	0.000452988	2.27E-05	9.50E-08	5.50E-08	0.433417494	0.026712416
A vs C	5.38E-31	9.22E-06	1.97E-35	4.30E-09	2.86E-26	0.207555265	1.09E-22	0.135825939	2.73E-08	0.00410613	1.09E-29	0.223967991	1.11E-20
A vs D	3.04E-32	2.59E-06	2.86E-22	1.05E-06	7.17E-18	0.034168284	1.72E-18	0.000911169	4.74E-13	1.17E-08	2.57E-24	0.106004831	3.92E-19
A vs E	1.46E-54	9.27E-09	3.35E-23	1.67E-07	3.40E-16	0.000526097	2.22E-19	4.50E-06	5.08E-17	3.27E-10	3.04E-23	0.001076441	3.14E-20
A vs F	5.82E-88	5.56E-11	1.32E-32	2.95E-07	2.87E-22	1.94E-07	1.61E-26	3.50E-10	4.34E-25	9.19E-11	1.71E-34	0.000566666	5.77E-28
A vs G	2.07E-95	8.89E-08	1.63E-42	0.000394703	7.09E-32	2.27E-07	1.86E-37	5.30E-10	5.56E-34	7.37E-10	2.00E-44	0.000213041	8.09E-37
B vs C	9.15E-15	0.485878646	2.17E-16	0.511798685	9.61E-16	0.000101265	4.55E-12	0.000253361	0.010626935	0.601704572	5.61E-14	0.134081361	1.84E-14
B vs D	3.43E-22	0.080710237	1.53E-13	0.059005108	1.08E-12	0.641434244	6.07E-13	0.053192373	1.08E-07	0.000240213	7.74E-16	0.193961573	6.45E-16
B vs E	2.91E-43	0.003065024	8.25E-15	0.018268532	8.19E-12	0.049286071	4.24E-14	0.000743989	1.97E-11	9.38E-06	1.04E-15	0.00386358	2.37E-17
B vs F	3.13E-74	0.000108483	2.80E-23	0.020351145	5.12E-17	0.000365736	2.17E-20	8.00E-07	7.47E-18	6.33E-06	4.79E-25	0.00207306	9.86E-25
B vs G	2.19E-87	0.001232177	1.01E-35	0.175165681	3.38E-27	6.67E-05	1.86E-32	2.54E-07	2.23E-27	2.63E-06	2.13E-37	0.000772669	1.29E-34
C vs D	7.18E-06	0.044187397	0.030610095	0.168135481	0.062714341	0.013078079	0.008190549	0.000184894	0.00065767	0.000369106	0.00132037	0.047223905	0.00185864
C vs E	8.60E-19	0.001203918	0.003175023	0.052609609	0.036896917	0.000177582	0.000735916	1.17E-06	3.85E-07	1.69E-05	0.00037514	0.000673272	6.60E-05
C vs F	5.48E-40	4.01E-05	4.12E-07	0.058516	0.000333396	9.76E-08	4.47E-07	6.57E-11	9.16E-12	9.52E-06	9.48E-09	0.000302341	1.24E-08
C vs G	7.46E-63	0.000405072	1.38E-18	0.266364718	4.50E-12	8.37E-08	2.90E-18	7.82E-11	8.42E-22	4.24E-06	2.52E-21	0.000217853	2.07E-19
D vs E	5.99E-05	0.283365385	0.480332235	0.634944714	0.758384299	0.264599225	0.449868952	0.206834111	0.051366248	0.397657196	0.633991744	0.18065473	0.31583511
D vs F	2.22E-15	0.07345095	0.008434681	0.661304878	0.113913695	0.015956425	0.022171358	0.018063255	0.000565663	0.381546485	0.020881652	0.136519727	0.014527121
D vs G	2.46E-38	0.085752332	3.79E-11	0.998837185	2.42E-07	0.003231975	2.74E-10	0.002119069	1.27E-12	0.093457244	9.01E-11	0.035314142	2.11E-10
E vs F	8.74E-05	0.43595958	0.067505301	0.978124043	0.206756974	0.257638636	0.138429506	0.382527136	0.198045279	0.945812482	0.078630865	0.89409836	0.173969248
E vs G	2.70E-24	0.371456611	3.65E-09	0.736872197	1.79E-06	0.045805117	2.18E-08	0.073343129	7.06E-07	0.305686244	1.35E-09	0.30101928	1.62E-07
F vs G	2.67E-13	0.88720566	1.19E-05	0.674979303	0.000258233	0.273524209	1.10E-05	0.28094016	3.49E-05	0.278992531	2.83E-06	0.378939899	1.55E-05

Table 7.3. Wilcox tests conducted to ascertain whether the distributions of exploratory variables were significantly different across the seven FSCs. P values highlighted red are classified as insignificant ($p \leq 0.05$).

7.3.2. Fire Size Class PCAs

Following the result of the distribution analysis, highlighting the variables which show the most striking trends across the FSCs, the relative importance of the retained exploratory variables in determining the variance across the fire event's fire danger conditions for each FSC separately was examined.

Principal Component Analyses of the remaining exploratory variables were conducted for each of the seven Fire Size Classes separately. For all of the seven PCAs (except FSC C with BD), the first and second components were found to explain over the 80% variance required, using the cumulative proportion of explained variance criterion, and were therefore the only components retained for interpretation of the principal component loadings.

Figure 7.7 shows the bi-plots for each of the FSCs, displaying how the fire event PC scores group together within each FSC and the eigenvectors for each of the exploratory variables across the principal components. In addition to this, Table 7.4 shows the principal component loadings for the first and second components for each of the FSCs. BD was found to be increasingly determinant of the variance in the larger FSCs than the classes that represent smaller fire sizes (Figure 7.7). BD did not contribute to either the first or second principal components for FSCs A-C (Table 7.4). It did however represent the majority of the second principal components for FSCs D-F, and drove the majority of the variance in the first and second principal components for the largest fire size class, FSC G. This shows that BD was not determinant factor in explaining the variance in the data surrounding smaller fires but was increasingly more determinant across the larger fire size classes (Table 7.4).

Table 7.4. Principal component loadings across the seven separate FSC PCAs (with BD).

	Exploratory Variables	Principal Component 1	Principal Component 2
FSC A	BD	0.081419	-0.08814
	FE_FDR_SD	0.43962	0.006587
	FE_STL_SD	0.36498	-0.4412
	FE_IC_SD	0.73052	0.56985
	FE_ERC_SD	0.365	-0.6876
FSC B	BD	0.054185	-0.03108
	FE_FDR_SD	0.5371	0.25667
	FE_STL_SD	0.46333	-0.29982
	FE_IC_SD	0.56018	0.55765
	FE_ERC_SD	0.42441	-0.72958
FSC C	BD	0.13516	0.39202
	FE_FDR_SD	0.50855	-0.41061
	FE_STL_SD	0.54604	0.27681
	FE_IC_SD	0.43392	-0.57378
	FE_ERC_SD	0.48647	0.52142
FSC D	BD	0.24069	0.96649
	FE_FDR_SD	0.55343	-0.17723
	FE_STL_SD	0.55293	-0.14779
	FE_IC_SD	0.42683	-0.11164
	FE_ERC_SD	0.38454	-0.01346
FSC E	BD	-0.35589	-0.91349
	FE_FDR_SD	-0.37462	0.22191
	FE_STL_SD	-0.5197	0.26228
	FE_IC_SD	-0.40783	0.21547
	FE_ERC_SD	-0.5446	0.032665
FSC F	BD	0.30209	-0.88913
	FE_FDR_SD	0.43891	0.27359
	FE_STL_SD	0.47514	0.28667
	FE_IC_SD	0.45263	0.18553
	FE_ERC_SD	0.53429	-0.13414
FSC G	BD	-0.56161	-0.78514
	FE_FDR_SD	-0.4876	0.41594
	FE_STL_SD	-0.4189	0.39793
	FE_IC_SD	-0.37686	0.22536
	FE_ERC_SD	-0.35965	-0.03751

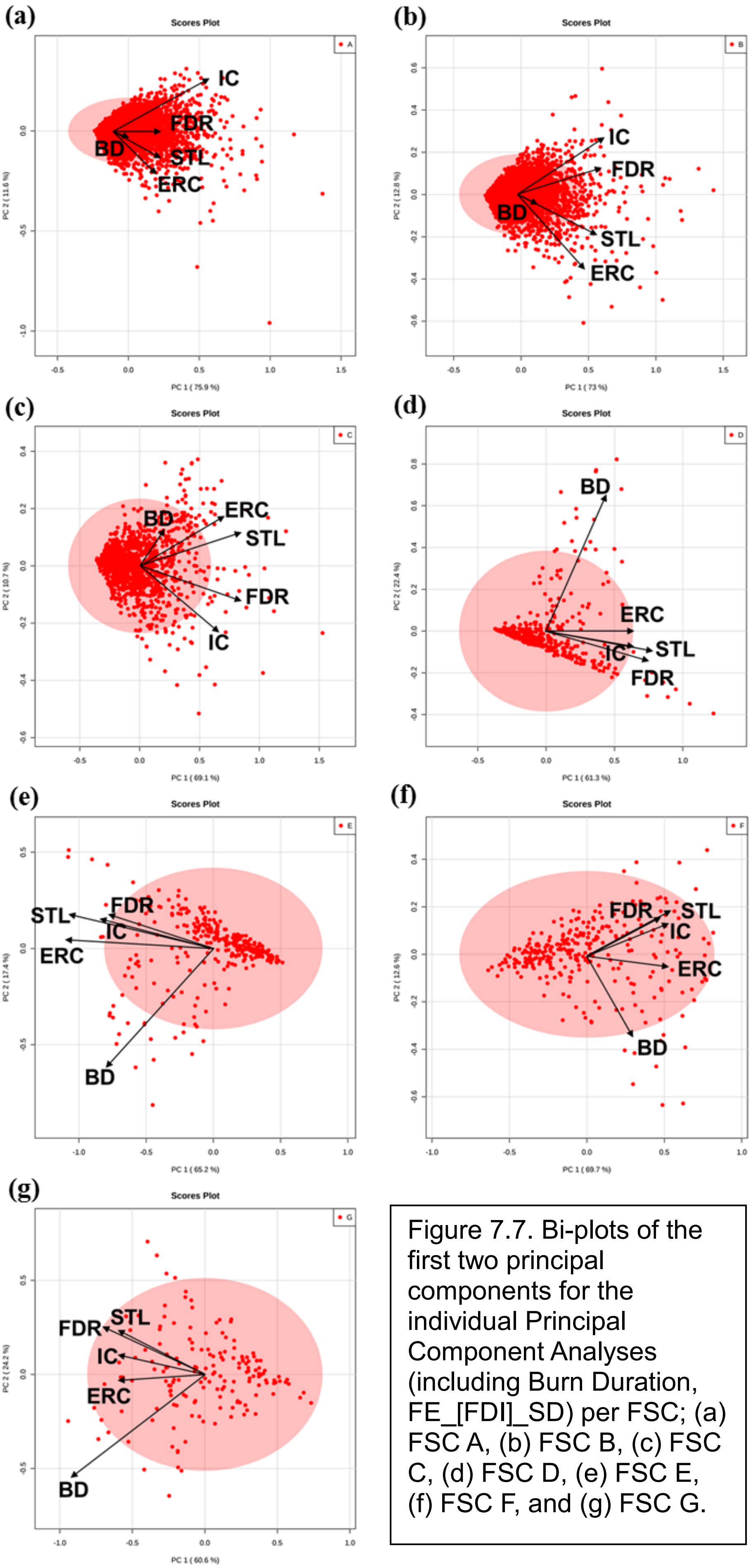

Figure 7.7. Bi-plots of the first two principal components for the individual Principal Component Analyses (including Burn Duration, FE_[FDI]_SD) per FSC; (a) FSC A, (b) FSC B, (c) FSC C, (d) FSC D, (e) FSC E, (f) FSC F, and (g) FSC G.

BD was then removed from the PCAs in order to see the relative importance of the remaining exploratory variables in determining the variance across the fire events fire danger conditions in the FSCs. The other exploratory variables become more important once BD is removed from the analysis, especially for the larger fire size classes. When you remove BD from the smaller fire size classes there is little change in the component loadings but there is a notable change to the loadings for large fire size classes. This may imply that fire duration is more determinant of larger fires than smaller fires.

Table 7.5 shows the principal component loadings for the first and second components for each of the FSCs with BD being omitted from the PCA. Additionally, Figure 7.8 shows the bi-plots for each of the FSCs, displaying how the fire event PC scores group together within each FSC and the eigenvectors for each of the exploratory variables across the principal components. It can be seen that different variable combinations were found to be determinant of each of the FSC's variance, with different variables corresponding to one-another in different directions across the PC scores.

Table 7.5. Principal component loadings across the seven separate FSC PCAs (without BD).

	Exploratory Variables	Principal Component 1	Principal Component 2
FSC A	FE_FDR_SD	0.44119	-0.00222
	FE_STL_SD	0.36577	0.44536
	FE_IC_SD	0.73337	-0.56651
	FE_ERC_SD	0.36568	0.69333
FSC B	FE_FDR_SD	-0.53803	0.2552
	FE_STL_SD	-0.46401	-0.3018
	FE_IC_SD	-0.56107	0.55753
	FE_ERC_SD	-0.42475	-0.73003
FSC C	FE_FDR_SD	0.51419	-0.36743
	FE_STL_SD	0.55165	0.49162
	FE_IC_SD	0.43834	-0.66406
	FE_ERC_SD	0.48902	0.427
FSC D	FE_FDR_SD	0.57305	-0.37549
	FE_STL_SD	0.57081	0.42796
	FE_IC_SD	0.43971	-0.58188
	FE_ERC_SD	0.39044	0.58075
FSC E	FE_FDR_SD	0.40592	-0.37538
	FE_STL_SD	0.56074	-0.07424
	FE_IC_SD	0.43914	-0.53785
	FE_ERC_SD	0.57268	0.7512
FSC F	FE_FDR_SD	-0.46324	0.37507
	FE_STL_SD	-0.50219	0.14335
	FE_IC_SD	-0.47298	0.43096
	FE_ERC_SD	-0.55633	-0.80811
FSC G	FE_FDR_SD	-0.60991	0.27193
	FE_STL_SD	-0.53233	0.3655
	FE_IC_SD	-0.45027	-0.05727
	FE_ERC_SD	-0.37668	-0.88836

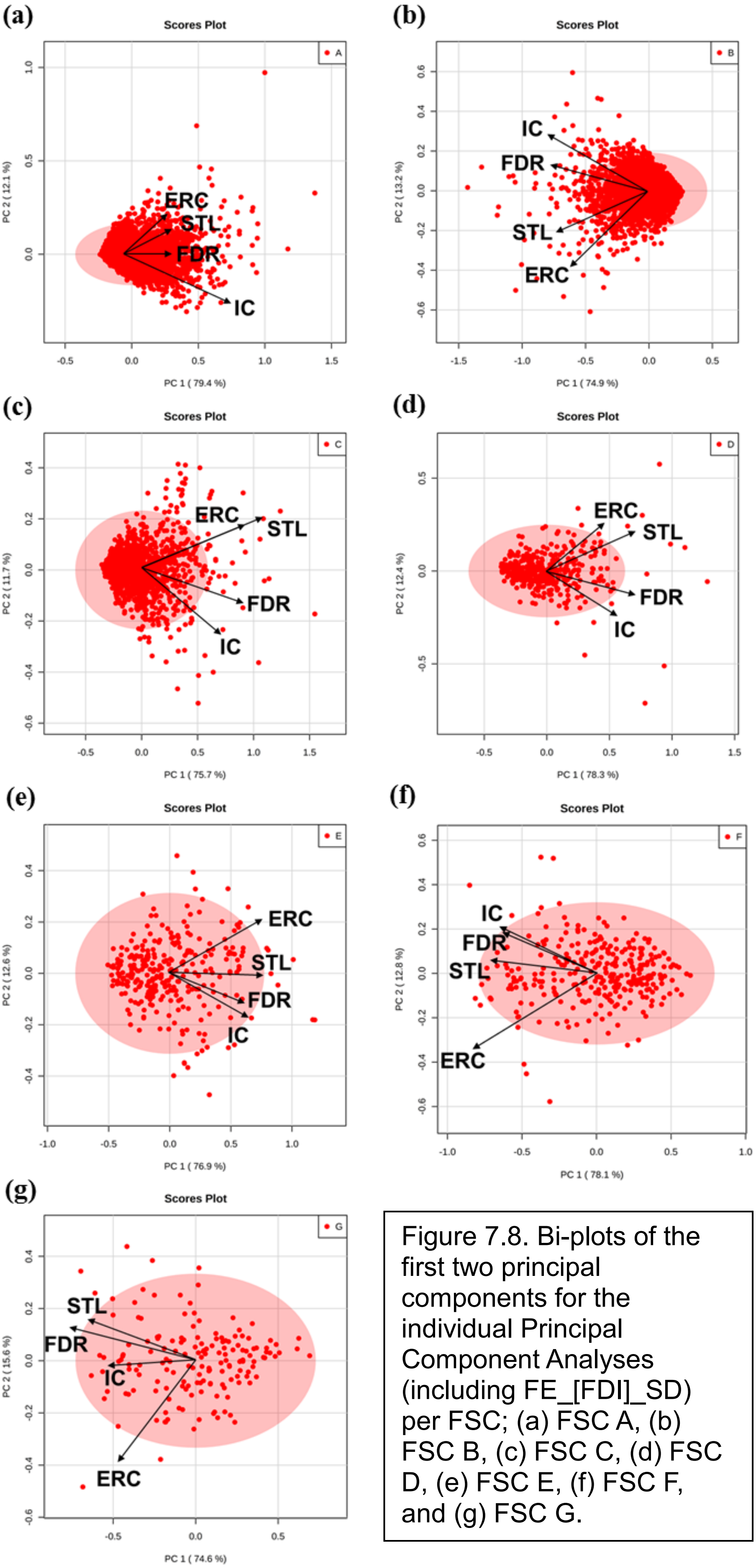

Figure 7.8. Bi-plots of the first two principal components for the individual Principal Component Analyses (including FE_[FDI]_SD) per FSC; (a) FSC A, (b) FSC B, (c) FSC C, (d) FSC D, (e) FSC E, (f) FSC F, and (g) FSC G.

For FSC A, FE_IC_SD and FE_ERC_SD appear to be the main factors driving variability within the fire events in FSC A (Table 7.5). The first principal component indicates that all four of the variables positively correlate with one another but are mainly constrained by FE_IC_SD. For the second component, two sets of the variables seem to act in opposite directions with the ERC_SD and STL_SD appearing to correlate to one-another positively, whilst IC_SD shows an opposite correlation, and FDR_SD exhibiting no correspondence in this component (Figure 7.8a).

For FSC B, the first component shows all of the four variables moving in the same direction, and positively correlating with one another, indicating that to the left hand side of the plot you would find fire events with higher PC1 scores corresponding to higher SDs of the four FDIs across each of the fire's burn duration (Figure 7.8b). However in PC2, IC_SD and FDR_SD diverge from STL_SD and ERC_SD, indicating that as PC2 scores increase you would see fire events with high IC and FDR SD but low STL and ERC SD, with the opposite being true with decreasing PC2 scores. The overall scores do however, group well within the 2 principal components but outliers displayed may be distinguished based on either their FDR and IC SDs or their STL and ERC SDs (Table 7.5).

For FSC C and FSC D, the division between FDR and IC, and STL and ERC SDs in the second principal component can once again be seen, following positive correlations between the four variables in the first principal component (Figure 7.8c and 8d, Table 7.5). However when considering the transition into LWFs (>300 acres), the fire events appear to group and cluster less well in the bi-plots (Figure 7.8e-g). The first principal component once again shows positive correspondences between the four variable, but across the second component, a similar set of divisions can be seen as with the previous FSCs, but instead of ERC and STL SD correlating together, the STL SD does not have much bearing on the second component.

For FSC F (Figure 7.8f), the fire events are grouped together even less but once again, the four variables correspond together across PC1 with ERC_SD constraining the data the most. PC2 however shows the SDs of IC, FDR, and STL grouping together and diverging from ERC_SD. In the bottom-left corner of the bi-plot for FSC F therefore you'll find fires with the largest of ERC_SD, and in the top left corner, you would find fire events with high SDs in FDR, STL, and IC.

Finally, for FSC G (>5000 acres, VLFS), the first component shows positive correlations between the four variables, with FDR_SD constraining the data in this axis. However for the second component, ERC_SD dominates with the other three variables explaining very little of the data in this component (Figure 7.8g). This plot is of interest because it would appear that for the largest fire size class, I find the fire events are mainly driven by FDIs representing aspects of fire behaviour through a management perspective; FDR and STL in PC1 (overall danger, and amount of preparedness needed) and ERC in PC2 (difficulty of control).

7.4. Discussion

Both Podur and Wotton, (2011) and Freeborn et al. (2015) commented that large fires are more likely due to a small number of high spread days that account for the majority of fire growth, this therefore makes the finding that the largest fire size classes appear to burn for longer durations surprising (e.g. Figure 7.2). Whilst, the category containing the largest fires (FSC G) has considerably longer mean and median burn durations than those in smaller fire size classes it should be noted that FSC G also has a considerably larger interquartile range than the other FSCs. This means that a substantial proportion of the fires in FSC G do overlap in terms of the range of burn duration with those in FSC E and FSC F. As such the largest FSC appears to capture fires that attain large sizes (>5000acres) both relatively rapidly and some that take considerably longer to attain large size.

Findings from Figures 7.3 and 7.4 are consistent with the assertion that average daily FDIs lose their ability to capture high-frequency fluctuations in these parameters (Preisler et al. 2008). All six measures of FDIs analysed (FDR, STL, IC, ERC, BI, SC) show limited mean variability across the seven fire size classes. This indicates that not only have model based reconstructions of FDIs determined this relationship (Brown et al. 2004, Preisler et al. 2008, Liu et al. 2013) but that this is now validated by this analysis of observed FDIs coupled to their respective concurrent fire activity. It is clear from both this analysis and that of Preisler et al. (2008) that the mean of experienced FDIs are not a good statistical descriptor of the fire danger conditions that lead to different fire size classes and that mean FDI conditions are incapable of providing a strong predictor of final fire sizes. This is likely to be particularly acute when averaging daily indices over longer time periods, especially for larger wildfires (FSCs E-G). This is unsurprising when considering Figure 7.9, which represents the daily ERC for a single fire event. The ERC can be seen to fluctuate on a daily basis over the entire fire's duration, however as indicated by the horizontal red dashed-line, the mean ERC for the fire fails to capture this behaviour. The SD of the ERC for the fire (vertical red line) better reflects the amount of variation in ERC during the fire and so provides a better representation of the fire danger conditions during this particular fire.

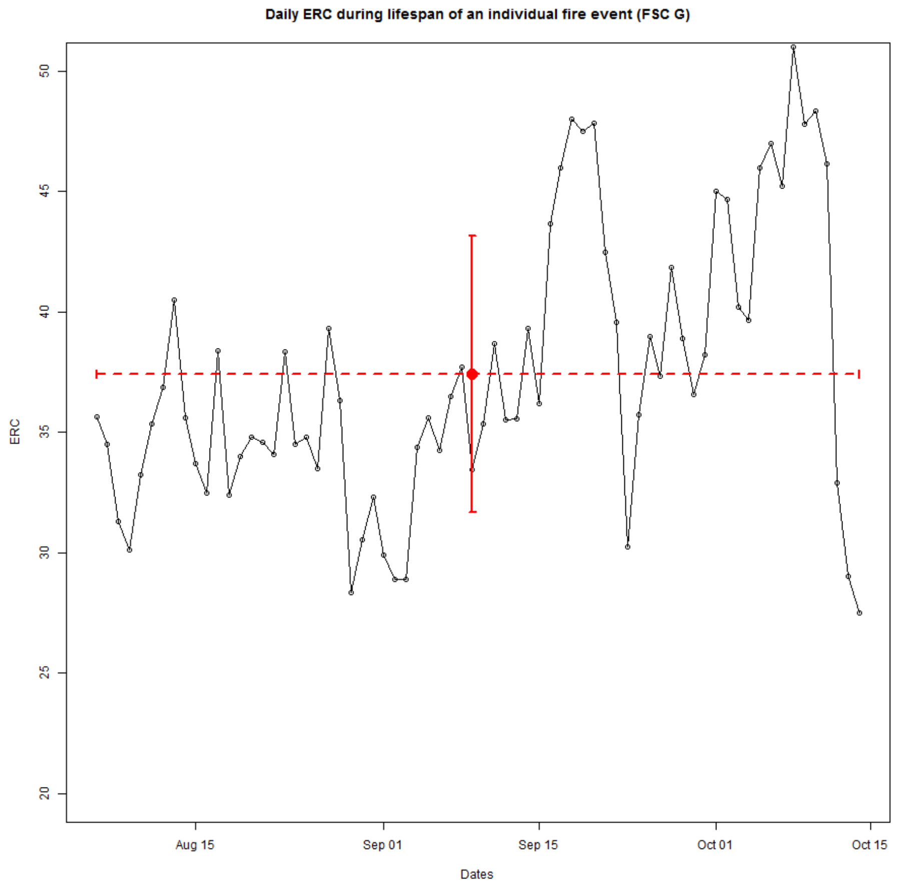

Figure 7.9. Example of the fire danger conditions (represented by ERC) present during an individual fire's burn period. The daily ERC (black line) is then summarised by the mean (dashed red line) and the standard deviation (solid red line) to summarise the overall fire danger conditions during the fire's burn period.

Existing research has noted the challenge of finding the appropriate temporal window over which to associate average fire danger and total burned area (e.g. Riley et al. 2013, Barbero et al. 2014a), in order to address this I have considered the SD of the daily FDIs during each fire event across the seven FSCs. Whilst this does not fully address temporal variation it does capture periods throughout which there are major deviations in FDI values from the mean (e.g. See Figure 7.9). Figures 7.5 and 7.6 display the distributions of the standard deviation of the daily FDIs across each of the fire's burn period across the 7 FSCs. The FDR, STL, IC, and ERC all exhibit increasing mean, median and interquartile ranges in SD with increasing fire size classes. This would infer that the more variable the fire danger conditions are during a fire event, then the greater potential they have to propagate into larger fires. This day-to-day variability in fire danger conditions is in line with anecdotal observations of sudden shifts in fire weather conditions during some of the most publicised fires in recent history; for instance the Yarnell Hill Fire (2013), the South Canyon Fire (1994), and the Oakland Firestorm (1991), all developed into larger than anticipated, and ultimately fatal fires due to sudden shifts in wind spread and resulting fire behaviour (Arizona State Forester 2013, Butler et al. 1998, Routley 1991).

However, interestingly the SC and BI do not display major differentiable SD values across the 7 FSCs with the normalised SD values staying below 0.1 (Figure 7.5e and 7.5f). The BI is derived from the SC and the ERC, to represent the difficulty of control of a fire in terms of rate of spread and the amount of energy available at the head of a fire (Schlobohm and Brain, 2002). The SC, which is a rating of the forward rate of spread of a headfire, is calculated using fine fuel moisture content (%), wind speed (ms^{-1}) and slope (%). Schlobohm and Brain, (2002) state that the SC is highly variable from day to day (Schlobohm and Brain, 2002) however, the distributions presented in Figure 7.5f appear to suggest that there is little variation in SC between the seven fire size classes. This may be due to the spatial-operational scale at which this indices is being applied. The spatial remit of all FDIs including SC from the NFDRS is to represent the near-worst burning conditions within a Fire Danger Rating Area (FDRA), and these can vary in size from 10^4 to 10^6 ha (Fosberg and Furman, 1971). However, the SC is closely based on Rothermel's 1972 spread model and can be seen in the NFDRS as a fire behaviour spread model being applied at greater spatial scales. Applying this over such a vast spatial area would therefore not represent true fire conditions accurately. For example, as mentioned in Chapter 5, the Rothermel model only considers fire spread in fine dead fuels and assumes that fire will spread without wind and irrespective of slope angle (Weise et al. 2016), suggesting that SC might tend to be over-predicted in smaller fires. More importantly large fires rarely only contain dead-fuel and are often driven by high winds therefore it could be that the Rothermel model tends to under-predict the total fuel available (i.e. no live fuel) and the rate of spread of the fires that end up burning to larger fire sizes. This would tend to level out of the apparent differences in SC between smaller and larger fires, such that less variation in SC is outputted by the NFDRS than might really be the case. Moreover, calculations of the NFDRS assume constant slopes and continuous fuel for each FDRA, two factors that are clearly unrealistic at such spatial scale. This would mean that issues with the application of the SC would then be compounded in the formation and calculation of the BI, thus accounting for the minimal variation in BI SDs across the fires in each of the 7 FSCs.

All other FDIs displayed in Figures 7.5 and 7.6; the FDR, STL, IC, and ERC, are potentially more applicable at the spatial remits of the NFDRS and corresponding FDRA for each reporting whether station as they seek to describe certain aspects of fire danger in terms of ignition, required fire business, and the overall state of the fuel in terms of fuel moisture. This may be why, given the spatial constraints of this study and the application of broad FDIs to specific, individual fires that were discovered within these areas, these 4 FDIs and their day-to-day variability, represented by the SD in FDI per FE, is a more suitable predictor of fires of differing final sizes.

From identifying that the burning duration of a fire and the day-to-day variability in fire danger conditions in certain aspects of fire danger, appeared to be good descriptors of fires of differing fire size class, the relative importance of these variables was explored for each of the FSCs separately to understand what combinations of variables were most determinant of fires of differing sizes.

From conducting the PCAs for each of the FSCs with the SDs of FDR, STL, IC, and ERC, and the BD, the influence of different variables can be seen to differ across the 7 classes of fire size. For all of the 7 FSCs, all 5 exploratory variables in Figure 7.7 are positively associated with one another in the first principal component, which on average accounts for 67.8% of the variance in each of the FSCs. In the second component, which on average accounts for 16% of the variance in each of the FSCs, there is a slight divergence between certain variables. In all fire size classes the majority of FDIs appear to contribute more or less equally to driving the variance of fire size within each fire size class (Figure 7.7). In FSC A however, the IC appears to account for the largest amount of variance in the dataset, suggesting that IC is a more important contributor to this fire size class than the other FDIs. This was first highlighted in Chapter 4, where low-mid IC values were shown to relate to trend in high FO, but low FFS (Figure 4.7). This indicted that the fires burning during these conditions were either at the low end of the spectrum and were perceived to not require suppressing (otherwise a higher IC value would suggest the contrary) or fires were ignited in the mid-range values of IC and were suppressed successfully. The contribution of burn duration typically increases throughout the fire size classes (e.g. length of the black arrows in Figure 7.7) as would be anticipated based on the strong correlation found between burn durations and fire size class (Figure 7.2). These additional Principal Component Analyses therefore supports the idea that larger fires burn for longer, and the final fire sizes are heavily due to an extended burn period.

Removal of BD from the PCAs show little changes in the contribution of the FDIs for the smaller FSCs (A, B, C, D), although the importance of IC as a key contributor to variance in FSC A remains. However, there substantial changes for the larger FSCS (E, F, G) (when comparing to the corresponding figure panels between Figure 7.7 and Figure 7.8). The remaining four exploratory variables are, once again, positively associated with one another in the first component (76.8%) as would be expected given their respective formation and calculation in the NFDRS. Additionally, for the small FSCs, the second component (13%) shows a divergence between the IC and FDR, ERC and STL.

For the larger FSCs (E, F, G) however, the ERC becomes a major driver of variance in both the first and second principal component. This substantial shift in importance of the ERC following the removal of the BD from the PCAs reveals that, independent of the fires burn duration, variability in the fuel state (represented by the ERC) is the next major driver of variance in fires of sizes greater than 300 acres (Figure 7.8e, f, g).

The relevance of the ERC (e.g. fuel conditions/state/energy content) to large wildfires is well established where the ERC has the perception of being a slowly-responding variable (Preisler et al. 2008). Moreover, the NFDRS suggests that “As a reflection of its composite fuel moisture nature, the ERC becomes a relatively stable evaluation tool for planning decisions that might need to be made 24 to 72 hours ahead of an expected fire decision or action” (Schlobohm and Brain, 2002, pg. 24). Factors such as wetter than normal antecedent growing seasons followed by dry conditions have been shown to relate to the occurrence of LWFs owing to the build-up of fire conducive fuels (Barbero et al. 2014). Moreover, Dennison et al. (2014) stresses the importance of severe drought conditions as also being an important contributor in the potential for large wildfires. However this is from a longer-term or seasonal perspective whilst the findings in this study exhibit how even the daily-variation in ERC is a key driver of larger wildfires. This makes intuitive sense because the ERC is driven by changes in moisture content of the various fuels present, both live and dead (Schlobohm and Brain, 2002) which do vary on daily timescales. This analysis suggests that these relatively small variations may be significantly more important than previously considered. For instance, greater variability in ERC throughout the duration of a fire would be expected to occur should there be rapid changes in wind speed and/or Relative Humidity (RH) over the duration of the fire. Whilst wind and slope do not enter into the ERC calculation, RH and fuel moisture are responsive to these factors therefore by definition ERC is also influenced by these conditions in reality even though this is not accounted for in the NFDRS model. It should therefore be anticipated that changes in wind and/or RH will also make a fire more difficult to suppress because the way in which ERC values would respond. ERC values represent the potential heat release per unit area in the flaming zone (fire intensity) (Schlobohm and Brain, 2002), therefore if the ERC behaves less predictably, this would make the containment of the fire more difficult for fire managers to allocate the necessary resources to and for firefighter to respond to on the ground. This can also be supported by anecdotal observations during significant fire events such as Yarnell Hill Fire (2013), the South Canyon Fire (1994), and the Oakland Firestorm (1991) in which factors such as wind and slope, resulted in substantial and sudden changes to fire intensity and making the fires harder to contain/manage. Therefore the accepted 'stability of the ERC' as a planning tool may need to be readdressed based on the finding that increased variability in ERC during fire events appears to link to large wildfires.

The findings I have presented here highlight the importance of variability of ERC on a high resolution temporal scale. This importance seems to be in accord with recent shifts in the development of the NFDRS that is beginning to aim for the generation of higher temporal and spatial resolution data and observations in order to better understand burning conditions across the conterminous US. For instance, TOPOFIRE (Holden and Jolly, 2011) provides high resolution fuel moisture data by accounting for the influence of aspect and slope on micro climates. Moreover sub-daily automated fire weather observations, and corresponding FDI calculation are highlighted by Jolly (2018, *pers comm*) as key improvements to the NFDRS that have been outlined in the recent 2016 revisions to the system. Sub-daily calculations of fire weather, and FDIs, with higher resolution fuel moisture data would greatly affect the representativeness and spatial resolution of ERC estimates. It will therefore be interesting to observe how sub-daily variations in ERC relate to large wildfires once enough data is gathered from the updated version of the NFDRS in due course.

One of the key rationales behind this study was to consider and identify an alternative utilisation for certain NFDRS FDIs in order to predict or pre-empt the development of large wildfires, based on the current fire danger conditions under which fires are already burning under. This set of analyses has not only identified the importance of the daily variations in ERC but also that our current understanding of the ERC does not fully enable good prediction of the development of large wildfires on a near-time temporal scale. Potential new utilisation of NFDRS outputs with further development of this work could aim to establish whether a 72 hr or 1-2 week temporal window of preceding fire weather and fuel state outputs from the NFDRS, would provide further details on the ‘current’ level of variability of ERC to develop a ‘LWF risk’ metric as part of the NFDRS. This could be threshold or percentile based, in order to give a relative-localised understanding of the current level of variability in ERC and what risk there is to the development of LWFs. Ultimately, understanding that LWFs are strongly related to daily variations in ERC could be extremely beneficial in terms of management capabilities and suppression actions.

7.5. Conclusions

Freeborn et al. (2015) states that ‘As of yet daily NFDRS indices and daily measures of wildland fire activity have rarely (if ever) been associated beyond the discovery date. Consequently, the underlying daily relationships between fire danger and persistent wildland fire activity remain largely unknown’ This study has potentially started to fill this research gap by using daily records of observed fire danger during fire event’s burn period to determine final fire sizes. This study first confirmed that larger fires do also burn for longer durations of time. More importantly however, this chapter has identified that the variability in FDIs across burn period of the fire is more determinant of its final fire size than the average fire danger condition. A number of FDIs that relate strongly to final fire size have been identified, however the ERC is the most significant FDI in determining wildfires greater than 1000 acres in size and may have the potential, with further work, to be implemented as a meaningful LWF risk metric within the NFDRS.

"You can't get runs in the pavilion"

Geoffrey Boycott

Chapter 8: Thesis Discussion and Conclusions

This thesis has assessed the ability of the NFDRS to portray fire activity across the USA on a national-scale and its operational effectiveness in mitigating fire activity. Moreover further analysis was conducted to assess how well selected NFDRS outputs characterise fires of differing final fire size, with a focus on LWFs. This chapter will discuss the findings and outcomes of the four main chapters by; assessing how well the NFDRS achieves its goals, and whether recent revisions to the system will alleviate any of the issues highlighted in this thesis. This chapter will then go on to discuss the implications of the findings from Chapter 7 with regards to further application of NFDRS outputs in LWF forecasting and management. Finally a brief discussion of whether knowledge of Fire Danger Rating Systems, such as the NFDRS, have utility in the Catastrophe risk and insurance industries.

8.1 Goals of the NFDRS

Fire danger rating systems attempt to pre-empt periods of heightened fire risk through forecasting and observing fire weather variables that are conducive to wildland fire ignition and propagation in order to aid fire management efforts by anticipating workload and facilitating resource allocation across wide spatial areas. The NFDRS in the US seeks to create a common lexicon of fire danger across the country to allow increasingly mobile fire fighters to communicate and conduct fire business in common terms and using single numbers to describe fire danger conditions simply and efficiently.

The NFDRS has been implemented across the US in order to facilitate cooperative action between various agencies, to ensure that mobile fire fighters are able to evaluate burning conditions in terms and figures of fire danger that have the same meaning in all areas of the country, and to assure that fire prevention warnings mean the same to people and the public in all areas (Hardy and Hardy, 2007). This has been achieved by basing the system and its numerous indices on only common aspects of fire behaviour and fire danger (Schlobohm and Brain, 2002).

There are four key characteristics that are fundamental to the NFDRS and historical US fire danger rating systems (WFAS, 2018e, Jolly, 2018, *pers comm*).

The system must be:

1. Modular – The conceptual design of the system needs to be modular in order for new science to be easily be added without altering the major structure of the system
2. Integrative – Fire danger indices must be integrated over both space (FDRA) and multiple time horizons (today – season – inter-annual)
3. Generalized – The same system must perform across a range of climates (i.e. it should work equally well everywhere)
4. Standardized – Fire Danger components and indices must have normalized index scales and be applicable across a spectrum of fire

management decisions. A common language' of fire danger must be maintained across all agencies.

These four aspects of fire danger ratings are key characteristics of the NFDRS and define its aims in terms of its desired structure, its functionality, and its operational utility. In the following I outline whether the NFDRS upholds these characteristics and/or fulfils its aims and objectives.

The desired modular design of the NFDRS appears to have well served its goals which has allowed successful implementation of updates to the system in both 1978 and 1988 and now with the its latest updates in the NFDRS2016. The modularity has allowed the outputs from the NFDRS to remain the same since its ‘creation’ in the early 1970s even though changes to input modules for better prediction have occurred through the earlier two sets of updates. New fire science understanding is currently being incorporated via the NFDRS2016 set of updates and revisions where the system is been stripped down to remove unnecessary complexity, again without changing the final outputs or compromising output accuracy. The NFDRS 2016 revision will be discussed more fully in the subsequent part of this chapter.

The ‘integrative’ aim of the fire danger indices has successfully allowed a range of a temporal perspectives of fire danger to be applied to a number of time-horizons. For example, the current operational outputs of the NFDRS are on a 1-day forecast which provides overall good utility for fire managers (e.g. Chapter 6). The daily observational data however, has also been utilised to generate seasonal forecasts in the western US e.g. Roads et al. (2005, 2010). It will be well worth extending such seasonal forecasts beyond the western US, to capture seasonal trends and improve management (e.g. Chapter 6). Furthermore, longer-term projections of fire danger, have utilised components of the NFDRS (ERC and KBDI, respectively) to estimate inter-annual fire potential according to future climate change predictions (e.g. Brown et al. 2004, Liu, Goodrick and Stanturf, 2013) highlighting the integrative design of the NFDRS is able to lend itself to prediction based outputs over a range of timescales when couple with additional information and approaches.

When considering whether the NFDRS is a generalized system and in successful in doing so, the findings of this thesis would indicate that this in fact not the case across the conterminous US. Jolly, (2018, *pers comm*) suggests that to be a truly generalized system the NFDRS needs to work/function equally across different climate zones and essentially work ‘everywhere’ equally. If the aim of the NFDRS is to portray, anticipate, and combat wildfire activity across the country then findings from Chapter 4 (Figure 4.3) would indicate that this is not achieved as the relationships between observed fire danger indices and metrics of fire activity (fire occurrence and final fire size) are not the same in all regions of the country. The FDIs and fire activity do display strong positive relations in the western part of the country however in a number of locations, almost in a mosaic effect, areas across the eastern and southern GACCs display substantially weaker relationships between NFDRS outputs and recorded wildfire activity. This would suggest that the NFDRS does not accurately portray fire activity in these regions for a number of reasons previously discussed in Chapter 4, namely; issues of regionally specific vegetation-climate relationships not being realised in the NFDRS, issues of the applicability of fuels models to southeaster, especially Floridian flora, and the contribution of human-caused fires to fire activity in the area. The first point regarding region-specific vegetation-climate interactions that are not represented in the NFDRS flies against the grounding concept of the NFDRS that outputs need to be based on common aspects of fire behaviour. This may be due to its lack of applicability in certain regions or ecosystems where key factors that drive fire potential and fire activity are not currently accounted for in the NFDRS's input models. Additionally, the findings presented in Chapter 6 suggest that the accuracy of the NFDRS's 1-day forecasts vary both spatially across the country and throughout the year for example in the western US where 35% of fire danger forecasts were found to be inaccurate over the study period, 2006-2013. Moreover, temporal inaccuracy is shown to increase in MAM and JAS, as well as through the winter in the case of the over-prediction of the STL. This further indicates that the NFDRS both from an observational standpoint and from a 1-day forecasting perspective would does not achieve high accuracy at all locations or consistently throughout the year.

When considering whether the NFDRS provides a true standardised means of predicting and communicating wildfire danger across the US it can't be denied that the outputs and indices provide just that. They are standardised into a common lexicon of fire danger that convey basic aspects of fire behaviour that are used to quantify fire conditions, from which raw numbers are standardised into index values based on the localised percentile distributions of the components for a given weather station or fire danger rating area. However this 'one size fits all' approach does not appear to fully capture the original rationale conceived by Harry Gibson (in 1922) or that of key contributors to the NFDRS past and present. Firstly, as previously mentioned, there are spatial inconsistencies in the relationships between the FDIs and FA across the country, notably with south-eastern regions indicating that the FDIs do not fully portray fire activity in these ecosystems or climate zones. Secondly, Chapter 6 (Figures 6.5 – 6.10, 6.12) indicates that there is a disconnect between the accurate (or inaccurate) forecasting of FDIs and variability in wildfire activity. One would expect that increased forecasting accuracy, both daily and temporally throughout the year, ought to allow the necessary fire management practices and efforts to put in place leading to decreased final fire sizes during peaks in fire activity. Whereas increased forecasting inaccuracy ought to lead to poor management and fires that might likely run out of control leading to larger final fire size. Whilst these expected relationships are consistent over the national scale for some FDIs examined (e.g. Figure 6.4 and 6.11), when conducting the same analyses spatially across the US, the large proportion of locations that do not display any significant relationships between accurate (or inaccurate) forecasting and fire activity suggests that the NFDRS is not being fully utilised or relied on as an operational tool through which to manage and control fires according to the forecasted fire danger conditions. Alternatively, it may be that in some cases fires that are considered to be burning during low fire danger conditions may be allowed to burn and become larger for fuel management purposes. This suggests that perhaps the common lexicon of fire danger may be achieved on a conceptual level, but that it may not be fully successful on an operational level, which brings into question the need or justification for a national system at all. It may be that one size does not fit all.

To further explore whether the NFDRS fulfils its aims, and gain an understanding of accepted applicability of the NFDRS from fire managers and NFDRS users from a range of regions, I compiled a short survey (~5-10 minutes) asking questions about how users utilise the NFDRS (on what timescales, what outputs are most useful) and whether users utilise other fire potential outlooks (such as the 7-day, monthly, 3-monthly Significant Wildfire Potential Outlook from NIFC Predictive Services), and if they prioritise these tools over the NFDRS in their operations. The survey (https://goo.gl/forms/qOAvJFCIKDvZt5lX2) was sent out to the Principal Investigator for each Fire Science Exchange (FSE, excluding the Alaskan and Pacific exchanges as they are not within the conterminous US) in the Fire Science Exchange Network (https://www.firescience.gov/jfsp_exchanges.cfm).

The creation of the survey was inspired by a conversation with an ex-Floridian fire manager and fuel technician who described what factors where most determinant of fire danger in the state of Florida given their experience. From this conversation it became clear that he and colleagues saw that the NFDRS merely as a ‘tick box’ exercise in which certain actions were needed to be completed from an ‘official procedure’ standpoint and not from an operationally useful perspective (Kunce, 2017, *pers comm*). Factors such as the level of the water table, longer-term fuel moisture (e.g. importance of 1000hr fuels), and topography were highlighted as key drivers of fire danger in the region as opposed to any of the output components from the NFDRS (Kunce, 2017, pers comm). This may indicate that the aforementioned selected ‘common’ aspects of fire behaviour that are the building blocks of the computed FDIs may have less relevance in these regions, thus bringing into question the applicability of a ‘one-size fits all’ national system. Even though the metrics of fire danger are common across the country, the way they are uniformly constructed with regards to key aspects of fire behaviour may be less relevant in some areas of the country such as the east and southeast where other factors may be more determinant of fire danger. Moreover, when the discussion moved onto the feelings towards the 40 current fuel models, the opinion of Kunce, (2017, *pers comm*) was that none of the current fuel models accurately represented any of the Floridian flora due to its endemic nature. This fuel issue may have been a part of the root causes of ‘mistrust’ in the system. These anecdotal sentiments do seem to mirror some of the findings from Chapter 4 and 6, and appears to highlight shortcomings of the aims for a generalized and standardized NFDRS across the country.

Seven responses to my survey were received that represented six of the Fire Science Exchanges which included the Northern Rockies FSE, the Northwest FSE, the Southern Rockies FSE, the Great Basin FSE, the North Atlantic FSE, and the Southern FSE. The information gathered from the question responses from the Southern FSE mirrored the sentiments of Kunce (2017, *pers comm*) in that the KBDI is the only FDI utilised from the NFDRS in much of the southeast owing to its measurement of drought conditions and being a strong long-term fuel moisture proxy. Moreover, the Southern FSE responses also noted that other fire potential outlooks were in fact utilised in preference to NFDRS outputs, and these focussed once again on drought indices. Responses from the more western US FSEs (Northwest, Northern Rockies and Southern Rockies) indicated that the NFDRS’s ERC as well as 1000-hr fuel moisture were two key components from the system that are used on a daily and seasonal basis for both fuel treatment and active fire management purposes from April to November. These responses support the successful use of the NFDRS in the western parts of the US with the strong relationships displayed between FDIs and fire activity in Chapter 4 (Figure 4.3) and the strong correlation between forecasted and observed FDIs in Chapter 5 (Figure 5.2). However across all responses, all noted that they utilised alternative sources of fire weather and fire danger outlooks in their day-to-day operations, with the majority highlighting that they use these alternative sources either with equal weighting as the NFDRS or in preference to the NFDRS. This may explain why there are a high number of insignificant relationships displayed between levels of accurate forecasting of FDIs and fire activity (Chapter 6, Figure 6.12) as not all fire managers are reliant on the outputs of the NFDRS and so inaccurate forecasting in this one-of-many fire weather outlooks may not have much bearing on potential miss-management or consequences of concurrent wildfire activity.

Owing to the lack of reliance on the NFDRS in regions such as the southeast of the US, where the feeling is that factors such as KDBI, hydrology, and 1000-hr fuel moisture drive fire activity, future analyses could consider re-running the analyses presented in Chapter 4 by utilising these variables alone from the NFDRS and spatially relate these variables to records of fire activity for the region. This would produce an alternative version of Figure 4.3 where monthly-means of KBDI and 100-hr fuel moisture could be correlated with monthly totals of fire occurrence and final fire size. This would provide a platform from which to assess whether these described factors do in fact produce stronger correlation coefficients than those already displayed between the FDR, STL, and IC, and the occurrence of fire and their final sizes (Figure 4.3). Similar applications of the frameworks of analysis from Chapter 4, 5, and 6, could also be applied to the other fire weather/ fire danger outlooks that stated to be operationally useful to fire managers across the country, either on equal weighting as the NFDRS outputs or in preference to them.

To summarise, key parts of the aims and objectives of the NFDRS are not fully realised across the country and to a degree bring into question the applicability of the national-scale based assessment of fire danger using only common aspects of fire behaviour to anticipate, portray, and combat wildfires across the conterminous US. The aforementioned NFDRS 2016 revisions may in fact address some of spatial inconsistency in model outputs and operational usage of the NFDRS through the proposed revisions. This will be examined in the next section of this chapter.

8.2. NFDRS 2016

NFDRS 2016 is the latest update for the NFDRS where a set of revisions are currently being implemented into the NFDRS after nearly 40 years of the previously ‘static’ version. The main drivers for revisions are based around the system remaining essentially the same since 1978, the system being too complex, fire danger expertise being diminished and that most fatality investigations cite a lack of knowledge of local fire danger as contributing factor (Jolly et al. 2015b). In September 2014 the National Wildfire Coordinating Group Executive Board meeting approved three updates to the system:

1. Incorporate the Growing Season Index (GSI, Jolly et al. 2005) to compute live fuel moistures
2. Incorporate the Nelson Model to compute fine dead fuel moisture on a sub-daily scale
3. Reduce the number of fuel models in the NFDRS

The Growing Season Index developed by Jolly et al. (2005) is a meteorologically based phenology model that predicts seasonal changes to live fuels (WFAS, 2018f). The model is based on day length (photoperiod), evaporative demand (vapour pressure deficit) and minimum temperatures (Jolly et al. 2005). The index indicates periods of increasing live fuel moisture and periods of moisture stress, and these estimates are more accurate than the current NFDRS calculations when compared to measured values (WFAS, 2018f). The existing NFDRS live herbaceous and woody fuel moisture models in the NFDRS have been cited as the weakest component of the system (WFAS, 2018f). The system allows highly variable live fuel moisture to span multiple fire danger classes where errors in live fuel moisture levels are likely to directly affect costs in safety and resources associated in the control and suppression of wildfires (Weise et al. 1998). The issue with the NFDRS live fuel moisture models is that the model is based on meteorological variables which relate to fuel moisture, but do not account for soil moisture which is a key driver of live fuel moisture (Qi et al. 2012), especially in the absence of additional precipitation (Brain, 2000). The proposed implementation of the GSI has been stated to significantly improve fire danger rating in areas where live fuels dominate even in long-periods of drought (WFAS, 2018f) (e.g. chaparral, Weise et al. 2016). However, the GSI appears to be driven solely by meteorological factors so may incur the same shortfalls as the previous models utilised in the NFDRS. Only through future analysis of the new version of the NFDRS will it be able to assess whether this will be a successful addition.

It is further suggested that the GSI will provide the improved live fuel modelling needed for the south-eastern states to increase their confidence in fire danger outputs from the NFDRS (WFAS, 2018f). This is in accord with the findings in Chapter 4 (Figure 4.3), where FDIs from the NFDRS were found to correspond weakly with metrics of fire activity, indicating that the two sets of data are decoupled in the Southern and Eastern GACCs. In Chapter 4 it is suggested that these weaker relationships could be due to issues surrounding the NFDRS's response to episodes of drought in humid conditions (Burgan 1988) or it could be that the majority of fires in this region are due to debris burning ignitions (Figure 4.5). The importance of live fuel moisture in the south-eastern states further relates to the anecdotal evidence from Floridian fire managers that question the applicability of NFDRS outputs and fuel models to their region due to previous iterations of the NFDRS neglecting the role of soil hydrology in influencing fire potential.

The second part of the NFDRS 2016 revisions are the implementation of the Nelson Model (Nelson, 2000) to calculate fine dead fuel moisture in place of the previously utilised Fosberg fuel moisture model (Fosberg and Deeming 1971). This development epitomises the desired transition from a somewhat subjective system to a truly analytical system, which was the ultimate goal in the original inception of the NFDRS (Hardy and Hardy 2007). The Fosberg fuel model utilises once-a-day calculations (~1pm LST) and requires manual entry of 'state-of-the-weather' and 'fuel wet' codes by the fire managers, which are subjective measures of meteorological (cloudiness) and fuel conditions (Fosberg and Deeming 1971). The Nelson Fuel Moisture Model on the other hand is designed to use frequent sub-daily weather observations (temperature, relative humidity, solar radiation, and precipitation) to compute fine dead fuel moisture (1-hr and10-hr) (Nelson, 2000). This will calculate fine dead fuel moisture 4 times a day (365 days/year) through an automated process that utilises hourly weather observation data from the RAWS network (Hardy and Hardy 2007). Following extensive validation of the Nelson model (Carlson et al. 2005a, 2005b, Carlson et al. 2007), the model has been shown to be a significant improvement on the existing Fosberg model for the 1-hr and 10-hr fuel moistures and can now be utilised for any diameter/time lag fuel (Carlson et al. 2005b). The full implementation of this automated-sub-daily calculation of fine fuel moisture is still ongoing (Jolly, 2018 *pers comm*) with data being recorded since 2010 to facilitate comparisons with the still currently operational Fosberg model outputs (WFAS, 2018f).

The future implementation and utilisation of the automated sub-daily (4-times a day) observations of fire weather and the calculation of dead fuel moisture through the Nelson model may alleviate some factors attributed to the inaccuracy of the 1-day forecasts of fire danger highlighted in Chapter 5, and the subsequent weaker relationships between forecasted FDIs and fire activity (Figure 5.7). The over- and under-forecasting of fire danger conditions were highlighted to be potentially owing to three factors; the fire weather forecasts from the National Weather Service, the resulting derived fuel state, and the manner in which observations of fire weather (and the derived fuel state) are conducted on a daily basis. The 1pm LST fire weather observations are the ‘jumping off point’ from which the forecasts are established. This last issue could potentially be resolved by the automated sub-daily fire weather observations as they could better record variations in fire weather and fuel temperature throughout the day (Countryman 1966, Schroeder and Buck 1970).

Owing to the Nelson model outputs reproducing observed dead fuel moisture across 1-hr, 10-hr, and 100-hr better than the Fosberg NFDRS dead fuel moisture model (Carlson et al. 2005b), the Nelson dead fuel moisture model may alleviate some of the spatial inconsistencies highlighted in Chapter 4 and the issues of the fuel models’ responses to 1-day forecasts in fire weather (Chapter 5). The issues of over- and under- prediction of fire danger conditions during MAM, due to green up and the role of live fuel moisture, and in JAS, due to the constrained calculation of dead fuel moisture in the summer (Brain, 2000), could be resolved by the implementation of the Nelson Model, in unison with the incorporation of the GSI, through better responsiveness of fuel moisture (live and dead) to seasonal changes in precipitation and the timing of snow melt (Brown et al. 2004, Westerling 2016).

However to assess the success of the future implementation and utilisation of the Nelson Model, operationally, future assessment could contrast fire danger outputs from the current Fosberg dead fuel moisture model and the Nelson model using a similar scheme of analysis presented in this thesis. Once a long enough record of Nelson model outputs have been gathered across the country, by coupling this data with overlapping records of fire activity (sourced from updated records of the USFS FPA FOD; Short, 2017) these proposed assessments could be achieved.

The 3rd proposed revision in NFDRS 2016 is the reduction of the number of fuel models utilised by fire managers in the NFDRS. In the original 1972 version of the NFDRS, 9 fuel models were utilised in the system. During the 1978 and 1988 revisions this number was essentially raised to 40 fuel models when including the 1988 versions of the 20 1978 fuel models. This was done in order to appease issues of responsiveness to drought in humid environments in regions of the south-east, as well as with the assumption that models with subtle differences would yield increased accuracy in the fire danger outputs produced. More recently the ERC was computed using 10 years of fire weather data and applied to the original (1978) 20 fuel models. The ERC outputs from the various fuel models were then cross-correlated and were found to be highly correlated with each other (Jolly et al. 2015b). These data were then analysed using cluster analysis and 5 resulting groupings of the fuel models became evident, representing the following fuel types; Grass/Shrubs (W), Grass (V), Brush (X), Timber (Y), slash (Z) (Jolly et al. 2015b). These were used to form a new set of fuel models for the NFDRS 2016. The new NFDRS 2016 fuel models and their equivalent models from the 1978 system can be seen in Table 8.1. The revised 2016 fuels models show very strong (>0.98) correlation scores when correlated with their constituent-previous 1978 fuel models, it is believed that the utilisation of these new 5 fuel models will not reduce or affect the accuracy of NFDRS outputs but will contribute to the reduction of complexity in the system and allow fire managers and NFDRS users to understand and utilise fire danger outputs more readily in the field (Jolly, 2018 *pers comm*). Thus alleviating the trend in a reduction of fire danger expertise. To ultimately assess whether this claim is true, as aforementioned above, re-analysing the NFDRS's FDIs using the new fuel models (and GSI and Nelson dead fuel moisture model) against concurrent fire activity across the conterminous US, under the assessment framework presented in this thesis, would provide an indication of improvement if results are compared and contrasted with the findings of this thesis where the current NFDRS has been assessed.

Table 8.1. NFDRS 2016 fuel types and fuel models and their equivalent fuel models from the 1978 system, adapted from (Jolly et al. 2015b).

NFDRS 2016 Fuel Type	**NFDRS 2016 Fuel Model**	**Equivalent NFDRS 1978 Fuel Model**
Grass	V	A, L, T
Grass / Shrub	W	R, S, C, D
Brush	X	B, F
Timber	Y	G, H, N, P, O, Q, U, E
Slash	Z	I, J, K

Although the incorporation of the GSI and the Nelson dead fuel moisture could potentially address some of the seasonal fuel moisture issues raised in the current analysis, I am not convinced that the simplification of the fuel models will have a direct impact on the accurate representation of fuel conditions across the country. The fuel models are essentially not changing, but are being simplified, meaning that the outputs from the new system in isolation from the other revisions would still have the same drawbacks evidenced in this analysis. For instance, the lack of responsiveness to daily fire weather forecasts or the role of live fuels in the prediction of fire danger in some fuel types. Moreover it should be noted that as forest type and age are predicted to change across the landscape in the future (Stephens et al. 2013) future iterations of the NFDRS will need to respond to changing fuel conditions, both in the composition of fuels but also their distribution across the country (Walding and Belcher, *in prep*). In order to accommodate these future changes the NFDRS fuel models will need to be constantly reviewed and updated in order to continue to accurately represent broad fuel state conditions over wide spatial scales. The recent 'revisions' of the fuel models are unconvincing in their ability to better represent fuel conditions across the country at present, further improvement will certainly be needed in the near future, at a rate faster than every 40 years, to revise and produce fuel models that will be relevant to future fuels.

Overall the NFDRS 2016 updates and revisions aim to reduce the complexity of the system, increase its automation, and increase its data output (both in terms of volume and consistency in reporting), without compromises to output accuracy. These aims in turn will facilitate quicker and easier training about, and uptake of, fire danger indices and outputs by fire managers and fire fighters for use in their daily and seasonal outputs. This may ultimately impact the efficiency of fire management practices in the allocation of resources nationwide, increase the success rates of fire suppression activities, facilitate more fuel management programs, and ultimately ensure fire fighter safety. In order to assess the success of the revised system once implemented in the future, the framework of analyses presented in this thesis could be re-applied to compare the FDI outputs from NFDRS 2016 with concurrent fire activity across the conterminous US and contrast the relationships and findings with those presented here.

8.3. Future utility of the NFDRS

In light of future management of forests and fires, Stephens et al. (2013) suggests that people living in forests must be prepared rather than relying solely on fire departments. Through the simpler nature of the NFDRS 2016, more accurate fire danger prediction could lead to more confident communication of wildfire risk to the public in promoting positive mitigation actions from landowners and forest residents. Furthermore to promote nationwide use of fire in fuel management, both now and in the future, North et al. (2015) suggest that changes in policy and resource-deployment decisions that support the use of fire as a management tool might better be made at the national level. Assuming that the NFDRS 2016 enhances uptake in regions that are currently less reliant on its outputs then this may make national cohesion stronger between regional management centres, which ought to aid changes in policy and resource-deployment decisions nationally.

With projected climate change, more fire conducive conditions are predicted in the coming decades with longer fire seasons (Jolly et al. 2015a), increased potential for very large wildfires (Barbero et al. 2015), and higher frequency of days with high risk of rapid wildfire growth (Luo et al. 2013). Despite this, policy makers will be challenged to not categorize all fires as destructive to ecosystems just based on long flame lengths and high tree mortality (Stephens et al. 2013). The suggested trends and predictions indicate that new strategies are needed in order to mitigate and adapt to increased fire in order to sustain forest landscapes (Stephens et al. 2013) and preserve ‘society’ in the long-term. This will require a potential steer away from a long history of successful fire suppression of fires, where 98% of fires are successfully contained or suppressed before reaching sizes greater than 300 acres (Calkin et al. 2005), and instead start to utilise fire through managing active fires and nationwide prescribed burn programs. Between 1998-2008, only 0.4% of wildfires were allowed to burn as managed wildfires (NIFC 2018a, North et al. 2015) owing to liability and causality risks with little tolerance of management error (North et al. 2015).

It may be that the NFDRS has a potential role in predicting wildfires and their management into the long term future. Given the forward looking nature of the revisions to the NFDRS, one starts to consider what other potential uses the system may have in the future in addition to the current utility of the NFDRS, especially in light of the challenges facing society in terms of climate change, changes in fuel dynamics, and the ongoing development of the WUI. Studies such as Brown et al. (2004) have utilised certain components from the NFDRS in association with Global Circulation Models (GCMs) to predict future fire danger. Brown et al. (2004) assessed decadal scale trends in ERC and climate from 1975-1996 and used this to generate future predictions of fire danger for the 21st Century. The southwestern region of the country is predicted to experience increased numbers of days above their ERC threshold ($40<ERC<59$, a value threshold that has strategic importance to fire management and policy makers) whilst states such as Idaho, eastern Oregon and Washington may see decreases in the numbers of days above the ERC threshold (Brown et al. 2004).

Such results highlight the potential of incorporating aspects of the NFRDS to make longer-term future fire danger predictions. However, findings from Chapter 4 indicate that NFDRS output do not have spatially consistent relationships with metrics of wildfire activity across the conterminous US (Figure 4.3). This is especially highlighted in the eastern and southern GACCs which display noticeably weaker correlations between all of the FDIs explored (FDR, STL, IC) with the occurrence of FFS. This finding indicates that the NFDRS model does not work equally in all areas of the US and so questions the portability of the NFDRS as a national system for use in future predictions of fire danger. This could be potentially resolved by the revisions being incorporated in NFDRS 2016 but these revisions need to be shown to resolve these spatial inconsistencies with further assessment of the NFDRS and fire activity. At this point in time however, there is little to support the idea that the NFDRS has strong correlations with wildfire activity across the entire US (Chapter 4). Therefore future modelling approaches that utilise GCM outputs to run calculations of future fire danger across the country should seek to address issues in the regions where the relationships are substantially weaker (e.g. eastern and southern GACCs) or be sure to test models against historic fire activity in all regions before generating future predictions.

In terms of aiding the take up and facilitation of fuel treatments and prescribed burning across the country, the NFDRS may have a potential role through experimental runs of fire danger using novel fuel models through the system in 'testing' scenarios. Finney et al. (2007) pose the question; "How do landscape-level fuel treatment patterns perform under weather scenarios more moderate than the extreme conditions specified in their design". The NFDRS could be utilised to these ends to run fire weather scenarios (historic or future) with new-proxy fuel models of potential fuel dynamics. By running the NFDRS with different fuel models and looking at the resulting fire danger under fuel models that represent pre- and post- ‘fuel treatment’ conditions, one could assess the likely success of proposed fuel treatments at the broad-landscape scale by taking into account the differences in fire danger between the different fuel conditions (represented by future fuels before, and after ‘fuel treatments’). These experimental ‘fuel treatments’ could be represented by changes in fuel load, mixing of live and dead fuels, and changes in fuel continuity or even changes in vegetation/fuel type and these can vary across a range of fuel treatment ‘success’ rates. Understanding the potential for landscape scale fuel treatments might be tested with novel fuel models slotted into NFDRS 2016 allowing them to be linked to fire danger outputs which may ultimately be of benefit to see net changes in fire danger and therefore wildfire potential.

Moreover using the NFDRS as a fuel-scenario experimental tool through hypothetical fuel model construction could also have relevance when considering shifting vegetation distributions in response to future climate change (e.g. climate-envelope modelling, Rehfeldt et al. 2012). For a given location or region, future fire danger could be assessed using future-hypothetical fuel models that represent how the vegetation/fuel may be in that specific region at a given point in the future. This might prove a powerful tool to anticipating future fire danger and enable better management of land where fire danger is potentially enhanced.

In light of the difficulty to motivate social responses to slow paced environmental transitions such as climate change, and long term fire threats (Stephens et al. 2013), the NFDRS may have a continuing role of communicating fire danger to the public in the future through mediums such as Smokey Bear and Fire Danger Maps. Public uptake and use of the NFDRS may also be aided through the revisions to the system suggested in NFDRS 2016, where regional inconsistencies may be alleviated and resolve potential issues of mistrust in the system. This mistrust is somewhat evidence from the seasonal and spatial patterns of debris burning across the country, with a particular focus on the southeast region of the country. From Chapters 4 and 6, the southeast has a high proportion of its wildfires caused by debris burning, and that the majority of debris burning caused fires occur in MAM when fire danger indices are over-predicted. This, in accord with the findings from Figure 4.3, that show weaker relationships between FDIs and FA in the southeast, may highlight that it is not only fire managers who do not utilise the NFDRS fully, but that the public may also not adhere to its warnings of fire danger. If NFDRS 2016 can resolve the issues the system has in this region through the implementation of the GSI and Nelson dead fuel moisture model, then the NFDRS may serve as a strong tool to convey shifts in fire danger and motivate social responses across the entire conterminous US.

To conclude NFDRS 2016 has the potential through the implementation of the GSI and Nelson fuel moisture model to alleviate some of the issues highlighted with the system in this thesis. However, future assessment is required in order to quantify how effective and successful the changes will be in terms of more accurate representation of the fire activity equally across the country, increased uptake in the use of the system as an operational tool and as a means to engage with the wider public with their wildfire danger, now and in the future. The revision of the fuel models in NFDRS is not convincing in its potential ability to be representative of fuel across the USA but could provide a simpler learning curve for new users of the system. Future applications of the system, to meet some of the challenges of the 21st Century, however, do focus around the potential use of the NFDRS and hypothetical fuel models to project future fire danger and assess the effectiveness of fuel treatment programs. Some aspects of potential utility of the NFDRS in terms of LWF management have been explored in Chapter 7 and will now be specifically discussed further in the subsequent section of this chapter.

8.4. Implications for the recognition of LWFs and their management

Large wildfires are of increasing concern across the USA owing to the amount of damage they cause, the total suppression expenditures needed to control them and their fatal nature. Some 98% of wildfires in the US are suppressed before they reach large fire sizes, however the remaining 2% burn under extreme weather conditions in forests with high fuel loads (North et al. 2015) and it is these fires that account for the greatest firefighting costs. Therefore, understanding LWFs is a fundamental necessity for fire management in order to ensure fire fighter safety, maximise awareness of LWF potential, and maximise the efficiency of control procedures. LWFs must by definition, be influenced by variables that operate across a broad range of temporal and spatial scales. For example, Jolly et al. (2015a) highlights that landscape-scale fire behaviour is determined by local weather conditions, but ecosystem-level wildfire potential is more appropriately associated with fire danger indices, which are representative of daily synoptic weather patterns. As such the transition from wildfires to large wildfires is influenced by a complex set of variables. Interestingly in the case of LWFs, whilst inaccurate forecasting appears to occur during periods when FO is at its greatest these inaccuracies do not necessarily lead to high FFS (Chapter 6, Figure 6.3). This suggests that large FFS may indeed results as a combination of factors (Brown et al. 2004).

Chapter 7 has shown that daily variability in fire danger indices relates to LWFs. Where daily variations in ERC during a fire's burn period are shown to be a key driver of variability in fire size, especially for larger fire size categories. By analysing a database that recorded LWF (>405ha/1000acres, FSC F and FSC G) covering the western US between 1984-2011, Dennison et al. (2014) found that for all western US ecoregions combined, the number of large fires increased at a rate of seven fires per year, while total fire area increased at a rate of 355 km^2 per year. Chapter 7 indicates that ERC is a considerable contributing factor in terms of characterising LWF and that increased variability in FDIs within a fires lifetime appears to have considerable influence as to whether or not a fire may achieve large extent. Whether or not this reconciles with the finding that large increases in LWF activity appear to be irrespective of fuel or seasonal variations in temperature and precipitation (Dennison et al. 2014) is questionable as the research I present here indicates that high-resolution variations in ERC link to LWFs and ERC ultimately relates to fuel type and relative humidity. The findings presented in this thesis are more in agreement with Brown et al. (2004) that suggest increases in reported average annual area burned are likely due to increased area protected, biomass accumulation due to fire suppression, and a greater tendency toward wet and dry extremes. As such they conclude that LWFs are the result of extreme fire weather conditions. Fire occurrence over large regions has been noted to relate to large-scale climate patterns where fires may occur synchronously across region where climate provides a strong signal (Swetnam and Betancourt, 1998). Interestingly increasing trends in drought severity have been linked to increasing trends in the occurrence of large wildfires and total area burned (Dennison et al. 2014). It is also noted that ecoregions that show increasing trends in the number of large fires and total fire area also display increasing trends in drought severity (Dennison et al. 2014). This highlights (as does Chapter 7) that variations in FDIs ought also to be reflective of the likelihood of LWFs as drought indices are an important input vector in the NFDRS.

It has been noted that anomalously dry conditions have a greater effect on fire danger (Agee, 1993, Swetnam and Betancourt, 1998, Donnegan et al. 2001) and that the impacts of large fires derive from the heterogeneous landscapes over which they spread in relation to their ignition sources under highly variable weather. The finding from Chapter 7 that ERC is the most significant FDI in relation to wildfires greater than 1000 acres must link to its role as fuel moisture proxy, where ERC is reflective of both relative humidity (%) and fuel type, that vary over the duration of a fire's lifetime time and across the heterogeneous landscapes through which they burn. ERC has been used as an FDI to estimate changes in LWF in a number of modelling approaches (e.g. Brown et al. 2004, Finney et al. 2011). For example, based on a decadal timescale, most of the western US was found to spend two months in the 40-59 threshold of ERC (Brown et al. 2004). Chapter 7 shows that daily variabilities within the presumed fire season are also important. For example, Figure 7.9 indicates that ERC may vary between approximately 27 and 52 during an individual fire's lifetime on a daily timescale. As such this finding indicates that future studies looking at the relationship between ERC and LWFs should not only consider the overall longer-term increases in the number of 40-59 ERC threshold days, (for instance, Brown et al. 2004 predict a two week increase in threshold days in the southwestern US towards the latter part of this century), but should consider the short-term daily variability of ERC toward the prediction and mitigation of future LWFs. Assessing thresholds of the NFDRS's ERC are considered to be of strategic importance to fire management and policy makers because the ERC serves as both an indicator of fire severity (the potential amount and extent of fire activity) and fire business (the decisions and economics of fire suppression and fuel treatments) to fire managers (Brown et al. 2004). It may be that ERC 'tipping points' (Lenton, 2011) exist across a range of timescales and that these should be identified in order to improve fire management.

As daily variability of ERC has been shown to characterise fires of different sizes, understanding an area's current value of ERC Standard Deviation (SD), relative to its specific FDRA/RAWS weather stations, could allow a means of portraying the current potential for larger wildfires, or in fact predict fire size potential. Future research could look to develop the findings presented in Chapter 7 to determine the relationships between the variability in ERC before a fire ignites, as well as potentially using a 7-day forecast to project the ERC's potential variability and relate this to the potential for LWFs to propagate. By focusing on fire danger (i.e. the ERC in this case), this should have the potential to reduce the complexity of the problem as it avoids needing to factor in numerous societal components of fire, land use and vegetation change (Brown et al. 2004).

It should be possible to gather historical records of fire activity from the USFS FPA FOD and daily-ERC values for specific weather stations, for a particular fire on a particular day (Fire $Event_{DOD}$) from the NFDRS and WFAS. Using the Date of Discovery (DOD, as a best representation of when a fire ignited) of a fire in a given location, one would be able to relate the variability of ERC conditions before the fire was discovered (e.g. ERC $SD_{DOD-7 – DOD}$), and the variability of ERC conditions in the first week that the fire potentially burned for (e.g. ERC $SD_{DOD – DOD+7}$). This would create a 14 day record of ERC variability, where precedent and concurrent ERC variability could be related to final fire size, or at least fire size class. If 'concurrent' fire danger conditions (ERC) were then able to be projected through the NWS in a similar fashion to the Significant wildfire 7-day to monthly outlooks, then there could be utility in using the NFDRS's ERC variability as a predictor of large wildfire potential.

Chapter 7 has already shown that the daily variability of ERC during the burning period of a fire is determinant of its final fire size. To take this research further, exploring the relationships between precedent and initial ERC conditions could provide a means of predicting the potential for LWFs.

8.5. Can such records of fire danger and fire danger indices be useful for the Catastrophe Risk and (re)insurance industry?

In order to enhance the impact of this thesis, over the last year I have actively made links with the CAT risk and insurance Industry, whom I'm hoping to work with in the future to develop this research further.

I have spoken on wildfire discussion panels at two insurance and catastrophe risk conferences, highlighting key drivers of fire activity across the US and noting the role fire danger indices and maps have in understanding a region's exposure, from a hazard/peril perspective, to wildfires. I have also discussed the role that prescribed burning has in current and future management of wildfires and some of the controversies surrounding it and previous fire suppression practices and agendas. The topic of future climate change and development has also been discussed, with highlighting trends in future fire potential and the expansion of the wildland urban interface in the coming decades. Some of the current needs and desires of the insurance sector have included but are not limited to gaining a greater understanding of urban conflagrations, smoke plume modelling, and ember transportation. The role of academia, especially given the knowledge base we have in the UK in fields such as fire ecology, fire modelling, and fire safety engineering, has been championed in an attempt to drive future collaboration between research institutes and the insurance sector to meet these desired aims.

Currently there are gaps in the market's appreciation and understanding of wildfires as major perils. Traditionally, the costs from wildfire events are extremely spiky and infrequent so the peril as of yet has not been given any great attention. To that end the current generation of major wildfire models are limited to covering just California and Australia. This is mainly owing to the limited amount of claims data being available beyond these regions as the majority of wildfire losses are associated with California in the US. However following the 2017 fire season, in which two major wildfire events occurred in California and major fires in Portugal, and other major WUI fires such as the Gatlinburg fires (2016) there has been a resurgent interest in wildfires with a wider spatial scope. Following the Tubbs and Thomas fires in northern and southern California in September and December, which have cost the insurance industry in excess of $14billion, many insurers and model vendors are asking whether they can assess their risk and exposure to this previously unknown/unrecognised, or ‘un-modelled’ peril.

At this point in time model vendors such as RMS, AIR, and Corelogic, are currently finishing their next generation of wildfire models with releases proposed for mid-late 2018. Although my current research may not be able to influence the development of these wildfire models due to their late-stage of development, the users of the models (i.e. client insurers and reinsurers) will need to enhance their understanding of wildfire risk and exposure in terms of their own view of risk and the way in which the modellers perceive and quantify wildfire risk. It is through this industry need that the research presented in this thesis could have value and be of potential use to insurers.

The first point of interest is the potential utility of the national fire danger maps, produced by the NFDRS and communicated through the WFAS, for constructing risk scores for different parts of the country. Whilst the Department of Insurance ultimately regulates risk scores and insurance pricing owing to the risk appetite of the market as a whole, there is potential for companies to set risk scores based on the meteorologically based outputs of fire danger maps. As the wildfire threat is constantly changing through the year, risk scores are now being regularly updated and fire danger maps, such as those produced through the NFDRS, could be of great use in re-setting risks scores through a fire season. Additionally, in order to set annual insurance premiums for property across the country, seasonal forecasts of fire danger have also been said to be of potential use for underwriters in the sector. Although there have only been a small number of studies that have sought to produce annual/seasonal forecasts of fire danger (Roads et al. 2005, 2010), other products such as the 'Significant Wildfire Potential Outlooks', which operate on a weekly, monthly, and 3-monthly, time horizon could be of use both from an inter-season and pre-season perspective and forecasting of wildfire risk.

The other aspect of the NFDRS that could be useful for the construction of wildfire cat risk models could be the far reaching database of fire danger and fire weather. These records, which are freely available-open access, could provide a climatology of fire weather/fire danger for any location across the country at a range of spatial scales. Given the outputs of this research, these data could act as proxies for wildfire activity and potential in certain regions and help represent and quantify the hazard component of a wildfire catastrophe risk model or just help underwriters gain a historical understanding of wildfire risk for a particular region.

Insurers have the potential to be key stakeholders in the relationships between wildfire and human populations through the incentivising of resident fuel management practices and the discouragement of further building development in some areas of the WUI owing to areas being too hazardous, as well as potentially mobilising policy reform through stakeholder pressure (Stephens et al. 2015, North et al. 2015). At present, insurers and catastrophe risk modellers are in need of better understanding of urban conflagrations, smoke plume modelling, ember transportation, whilst also needing a great appreciation of wildfire danger and exposure across the US, and their global portfolios. Aspects of my research, which has been presented in this thesis, could aid with the latter of the aforementioned needs with new utilisation of the NFDRS.

8.6. Thesis summary:

This thesis has found that overall the intrinsic process of the NFDRS do well portray fire activity across the USA although some areas of alarm have been highlighted. The NFDRS forecasts of fire danger have been found to vary in accuracy through the year and this appears to correspond to increases in wildfire activity on a national-scale, but not spatially explicitly across different regions of the US. The future utility of the NFDRS appears to hinge on its ability to adapt to projected changes in climate and vegetation dynamics, the first step of which is through the successful implementation of NFDRS 2016. Finally, variable fire danger conditions, most notably ERC, have been shown to be determinant of larger wildfires and through future research could be developed into a near-term predictor of large wildfire potential.

“It's not how good you look, it's how many you get”.

Geoffrey Boycott

Appendix II: Fuel Models of the NFDRS

Table A2.1 Fuel Model Definitions from the National Fire Danger Rating System (1978), from the National Wildfire Coordination Group, available at https://fam.nwcg.gov/fam-web/helpdesk/wims/nfdr.htm [Verified 15 May 2018].	
Fuel Model A	This fuel model represents western grasslands vegetated by annual grasses and forbs. Brush or trees may be present but are very sparse, occupying less than a third of the area. Examples of types where Fuel Model A should be used are cheatgrass and medusahead. Open pinyon-juniper, sagebrush-grass, and desert shrub associations may appropriately be assigned this fuel model if the woody plants meet the density criteria. The quantity and continuity of the ground fuels vary greatly with rainfall from year to year.
Fuel Model B	Mature, dense fields of brush 6 feet or more in height are represented by this fuel model. One-fourth or more of the aerial fuel in such stands is dead. Foliage burns readily. Model B fuels are potentially very dangerous, fostering intense fast-spreading fires. This model is for California mixed chaparral generally 30 years or older. The F model is more appropriate for pure chamise stands. The B model may be used for the New Jersey pine barrens.
Fuel Model C	Open pine stands typify Model C fuels. Perennial grasses and forbs are the primary ground fuel but there is enough needle litter and branchwood present to contribute significantly to the fuel loading. Some brush and shrubs may be present but they are of little consequence. Situations covered by Fuel Model C are open, longleaf, slash, ponderosa, Jeffrey, and sugar pine stands. Some pinyon-juniper stands may qualify.
Fuel Model D	This fuel model is specifically for the palmetto-gallberry understory-pine overstory association of the southeast coastal plains. It can be also used for the so-called "low pocosins" where Fuel Model O might be too severe. This model should only be used in the Southeast because of a high moisture of extinction.
Fuel Model E	Use this model after leaf fall for hardwood and mixed hardwood-conifer types where the hardwoods dominate. The fuel is primarily hardwood leaf litter. The oak-hickory types are best represented by Fuel Model E, but E is an acceptable choice for northern hardwoods and mixed forests of the Southeast. In high winds, the fire danger may be underrated because rolling and blowing leaves are not accounted for. In the summer after the trees have leafed out, Fuel Model E should be replaced by fuel Model R.
Fuel Model F	Fuel Model F is the only one of the 1972 NFDRS Fuel Models whose application has changed. Model F now represents mature closed chamise stands and oakbrush fields of Arizona, Utah, and Colorado. It also applies to young, closed stands and mature, open stands of California mixed chaparral. Open

	stands of pinyon-juniper are represented; however, fire activity will be overrated at low wind speeds and where there is sparse ground fuels.
Fuel Model G	Fuel Model G is used for dense conifer stands where there is a heavy accumulation of litter and downed woody material. Such stands are typically overmature and may also be suffering insect, disease, wind, or ice damage -- natural events that create a very heavy buildup of dead material on the forest floor. The duff and litter are deep and much of the woody material is more than 3 inches in diameter. The undergrowth is variable, but shrubs are usually restricted to openings. Types meant to be represented by Fuel Model G are hemlock-Sitka spruce, Coast Douglas-fir, and windthrown or bug-killed stands of lodgepole pine and spruce.
Fuel Model H	The short-needled conifers (white pines, spruces, larches, and firs) are represented by Fuel Model H. In contrast to Model G fuels, Fuel Model H describes a healthy stand with sparse undergrowth and a thin layer of ground fuels. Fires in H fuels are typically slow spreading and are dangerous only in scattered areas where the downed woody material is concentrated.
Fuel Model I	Fuel Model I was designed for clear-cut conifer slash where the total loading of materials less than 6 inches in diameter exceeds 25 tons/acre. After settling and the fines (needles and twigs) fall from the branches, Fuel Model I will overrate the fire potential. For lighter loadings of clear-cut conifer slash, use Fuel Model J, and for light thinnings and partial cuts where the slash is scattered under a residual overstory, use Fuel Model K.
Fuel Model J	This model complements Fuel Model I. It is for clearcuts and heavily thinned conifer stands where the total loading of materials less than 6 inches in diameter is less than 25 tons/acre. Again, as the slash ages, the fire potential will be overrated.
Fuel Model K	Slash fuels from light thinnings and partial cuts in conifer stands are represented by Fuel Model K. Typically the slash is scattered about under an open overstory. This model applies to hardwood slash and to southern pine clearcuts where the loading of all fuels is less than 15 tons/acre.
Fuel Model L	This fuel model is meant to represent western grasslands vegetated by perennial grasses. The principal species are coarser and loadings heavier than those in Model A fuels. Otherwise the situations are very similar; shrubs and trees occupy less than one-third of the area. The quantity of fuel in these areas is more stable from year to year. In sagebrush areas Fuel Model T may be more appropriate.
Fuel Model N	This fuel model was constructed specifically for the sawgrass prairies of south Florida. It may be useful in other marsh situations where the fuel is coarse and reedlike. This model assumes that one-third of the aerial portion of the plants are

	dead. Fast-spreading, intense fires can occur even over standing water.
Fuel Model O	The O fuel model applies to dense, brushlike fuels of the Southeast. O fuels, except for the deep litter layer, are almost entirely living in contrast to B fuels. The foliage burns readily except during the active growing season. The plants are typically over 6 feet tall and are often found under an open stand of pine. The pocosins of the Virginia, North and South Carolina coasts are the ideal of Fuel Model O. If the plants do not meet the 6-foot criteria in those areas, Fuel Model D should be used.
Fuel Model P	Closed, thrifty stands of long-needled southern pines are characteristic of P fuels. A 2- to 4-inch layer of lightly compacted needle litter is the primary fuel. Some small diameter branchwood is present but the density of the canopy precludes more than a scattering of shrubs and grass. Fuel Model P has the high moisture of extinction characteristic of the Southeast. The corresponding model for other long-needled pines is U.
Fuel Model Q	Upland Alaskan black spruce is represented by Fuel Model Q. The stands are dense but have frequent openings filled with usually inflammable shrub species. The forest floor is a deep layer of moss and lichens, but there is some needle litter and small-diameter branchwood. The branches are persistent on the trees, and ground fires easily reach into the tree crowns. This fuel model may be useful for jack pine stands in the Lake States. Ground fires are typically slow spreading, but a dangerous crowning potential exists. Users should be alert to such events and note those levels of SC and BI when crowning occurs.
Fuel Model R	This fuel model represents the hardwood areas after the canopies leaf out in the spring. It is provided as the off-season substitute for E. It should be used during the summer in all hardwood and mixed conifer-hardwood stands where more than half of the overstory is deciduous.
Fuel Model S	Alaskan or alpine tundra on relatively well-drained sites is the S fuel. Grass and low shrubs are often present, but the principal fuel is a deep layer of lichens and moss. Fires in these fuels are not fast spreading or intense, but are difficult to extinguish.
Fuel Model T	The bothersome sagebrush-grass types of the Great Basin and the Intermountain West are characteristic of T fuels. The shrubs burn easily and are not dense enough to shade out grass and other herbaceous plants. The shrubs must occupy at least one-third of the site or the A or L fuel models should be used. Fuel Model T might be used for immature scrub oak and desert shrub associations in the West, and the scrub oak-wire grass type in the Southeast.
Fuel Model U	Closed stands of western long-needled pines are covered by this model. The ground fuels are primarily litter and small branchwood. Grass and shrubs are precluded by the dense canopy but occur in the occasional natural opening. Fuel

	Model U should be used for ponderosa, Jeffrey, sugar pine, and red pine stands of the Lake States. Fuel Model P is the corresponding model for southern pine plantations.

Appendix III: Example of R code used for processing the data used in this thesis

The following screenshots of code exhibit how the fire activity and fire danger data (observed and forecasted) were processed from datasheets and onto 3D grids representing the conterminous US through the time period 2006-2013. The examples below display the code for daily-means of fire danger and daily-totals of fire activity being produced. This thesis utilized both daily- and monthly-summarized data, with the monthly-means and monthly-totals being processed in the same manner as the daily-means and daily-totals shown in this appendix.

RStudio Source Editor

example_of_code.R

Source on Save

```r
getwd()
setwd("D:\\Phd\\R\\FO_data_array")

##############################################################################################
##############################################################################################
#### Reading in the Fire Danger (Observed and Forecasted) and Fire Activity data

FA_data<- read.csv('D:\\Phd\\R\\Data_array\\FA_data_2006-2013.txt')
FA_data$Date <- as.Date(substr(FA_data[,3],1,10))

FDR_obsv_data <- read.csv('D:\\Phd\\R\\Data_array\\FDR_obsv_data_2006_2013.txt')
FDR_obsv_data$Date <- as.Date(paste0(FDR_obsv_data[,25],'-',FDR_obsv_data[,26],'-',FDR_obsv_data[,27]))

FDR_fcst_data <- read.csv('D:\\Phd\\R\\Data_array\\FDR_fcst_data_2006_2013.txt')
FDR_fcst_data$Date <- as.Date(paste0(FDR_fcst_data[,25],'-',FDR_fcst_data[,26],'-',FDR_fcst_data[,27]))

# 1136073600 - unix timestamp for start of Data TP - 2006-01-01
# 1388448000 - unix timestamp for end of Data TP - 2013-12-31


unique_dates <- as.Date(as.POSIXct(seq(1136073600,1388448000, by = 86400), origin = '1970-01-01')) # code for converting timestamp into dates


##############################################################################################
##############################################################################################
#### Creating Daily-Total FO and FFS Arrays

FO_Counts_grd <- array(NA, dim = c(x, y, 2922))
FS_Sums_grd <- array(NA, dim = c(x, y, 2922))

lons <- seq(-125, -60, by = 1)
lats <- seq( 25, 50, by = 1)

x <- length(lons)-1
y <- length(lats)-1

q=0

for (i in 1: x) {
  for (j in 1: y) {

    lon_FA = which(FA_data$longitude>lons[i] &  FA_data$longitude<lons[i+1])
    lat_FA = which(FA_data$latitude>lats[j] &  FA_data$latitude<lats[j+1])
    grid_FA = intersect(lon_FA, lat_FA)

    for (z in 1: length(unique_dates)) {

      FO_Counts_grd[i,j,z] <- length(which(FA_data$Date[grid_FA]== unique_dates[z]))
      FS_Sums_grd[i,j,z] <- sum(FA_data$fire_size[grid_FA][FA_data$Date[grid_FA] == unique_dates[z]])

      q=q+1
      print(q)
    }
  }
}
```

```r

########################################################################################
########################################################################################
#### Creating Daily-Mean Observed FDR, STL, IC, SC, BI, and ERC Arrays

FDR_obsv_mean_grd <- array(NA, dim = c(x, y, 2922))
STL_obsv_mean_grd <- array(NA, dim = c(x, y, 2922))
IC_obsv_mean_grd <- array(NA, dim = c(x, y, 2922))
SC_obsv_mean_grd <- array(NA, dim = c(x, y, 2922))
BI_obsv_mean_grd <- array(NA, dim = c(x, y, 2922))
ERC_obsv_mean_grd <- array(NA, dim = c(x, y, 2922))


lons <- seq(-125, -60, by = 1)
lats <- seq( 25, 50, by = 1)

x <- length(lons)-1
y <- length(lats)-1

q=0

for (i in 1 :x) {
  for (j in 1: y) {

      lon_FDR_obsv = which(FDR_obsv_data$Long>lons[i] &  FDR_obsv_data$Long<lons[i+1])
      lat_FDR_obsv = which(FDR_obsv_data$Lat>lats[j] &  FDR_obsv_data$Lat<lats[j+1])
      grid_FDR_obsv = intersect(lon_FDR_obsv, lat_FDR_obsv)

    for (z in 1: length(unique_dates)){

      FDR_obsv_mean_grd[i,j,z] <- mean(FDR_obsv_data$ratings[grid_FDR_obsv][FDR_obsv_data$Date[grid_FDR_obsv] == unique_dates[z]], na.rm = TRUE)
      STL_obsv_mean_grd[i,j,z] <- mean(FDR_obsv_data$STL[grid_FDR_obsv][FDR_obsv_data$Date[grid_FDR_obsv] == unique_dates[z]], na.rm = TRUE)
      IC_obsv_mean_grd[i,j,z] <- mean(FDR_obsv_data$IC[grid_FDR_obsv][FDR_obsv_data$Date[grid_FDR_obsv] == unique_dates[z]], na.rm = TRUE)
      SC_obsv_mean_grd[i,j,z] <- mean(FDR_obsv_data$SC[grid_FDR_obsv][FDR_obsv_data$Date[grid_FDR_obsv] == unique_dates[z]], na.rm = TRUE)
      BI_obsv_mean_grd[i,j,z] <- mean(FDR_obsv_data$BI[grid_FDR_obsv][FDR_obsv_data$Date[grid_FDR_obsv] == unique_dates[z]], na.rm = TRUE)
      ERC_obsv_mean_grd[i,j,z] <- mean(FDR_obsv_data$ERC[grid_FDR_obsv][FDR_obsv_data$Date[grid_FDR_obsv] == unique_dates[z]], na.rm = TRUE)


      q=q+1
      print(q)
    }
  }
}


########################################################################################
########################################################################################
#### Creating Daily-Mean Forecasted FDR, STL, IC, SC, BI, and ERC Arrays

FDR_fcst_mean_grd <- array(NA, dim = c(x, y, 2922))
STL_fcst_mean_grd <- array(NA, dim = c(x, y, 2922))
IC_fcst_mean_grd <- array(NA, dim = c(x, y, 2922))
SC_fcst_mean_grd <- array(NA, dim = c(x, y, 2922))
BI_fcst_mean_grd <- array(NA, dim = c(x, y, 2922))
ERC_fcst_mean_grd <- array(NA, dim = c(x, y, 2922))


lons <- seq(-125, -60, by = 1)
lats <- seq( 25, 50, by = 1)

x <- length(lons)-1
y <- length(lats)-1

q=0

for (i in 1 :x) {
  for (j in 1: y) {


    lon_FDR_fcst = which(FDR_fcst_data$Long>lons[i] &  FDR_fcst_data$Long<lons[i+1])
    lat_FDR_fcst = which(FDR_fcst_data$Lat>lats[j] &  FDR_fcst_data$Lat<lats[j+1])
    grid_FDR_fcst = intersect(lon_FDR_fcst, lat_FDR_fcst)

    for (z in 1: length(unique_dates)){

      FDR_fcst_mean_grd[i,j,z] <- mean(FDR_fcst_data$ratings[grid_FDR_fcst][FDR_fcst_data$Date[grid_FDR_fcst] == unique_dates[z]], na.rm = TRUE)
      STL_fcst_mean_grd[i,j,z] <- mean(FDR_fcst_data$STL[grid_FDR_fcst][FDR_fcst_data$Date[grid_FDR_fcst] == unique_dates[z]], na.rm = TRUE)
      IC_fcst_mean_grd[i,j,z] <- mean(FDR_fcst_data$IC[grid_FDR_fcst][FDR_fcst_data$Date[grid_FDR_fcst] == unique_dates[z]], na.rm = TRUE)
      SC_fcst_mean_grd[i,j,z] <- mean(FDR_fcst_data$SC[grid_FDR_fcst][FDR_data$Date[grid_FDR_fcst] == unique_dates[z]], na.rm = TRUE)
      BI_fcst_mean_grd[i,j,z] <- mean(FDR_fcst_data$BI[grid_FDR_fcst][FDR_data$Date[grid_FDR_fcst] == unique_dates[z]], na.rm = TRUE)
      ERC_fcst_mean_grd[i,j,z] <- mean(FDR_fcst_data$ERC[grid_FDR_fcst][FDR_data$Date[grid_FDR_fcst] == unique_dates[z]], na.rm = TRUE)

      q=q+1
      print(q)
    }
  }
}

```

116:1 (Untitled)

Appendix IV: Further details on data and methods employed in Chapter 4

Table A4.1 Details of the data utilised in Chapter 4 with information on how the data was processed and the variables created for analysis in this chapter.

Data Utilised	**Data Source**	**Original Format**	**Data Processing**	**Exploratory Variables Created**
Fire Occurrence (FO)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Monthly totals of FO were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the USFS FPA FOD, the number of fires that occurred per Grid Square, per month, could be calculated.	Monthly totals of FO
Final Fire Size (FFS, acres)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Monthly totals of FFS were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the USFS FPA FOD, the total number of acres burned from fires that occurred per Grid Square, per month, could be calculated.	Monthly totals of FFS
Observed Fire Danger Rating (FDR)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from	Monthly means of observed FDR were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the daily datasheets from the NFDRS, the mean observed	Monthly means of Observed FDR

		each weather station, observed weather data, and derived fire danger index values.	FDR could be calculated per Grid Square, per month.	
Observed Staffing Level (STL)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	Monthly means of observed STL were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period).Using the date, longitude, and latitude information from the daily datasheets from the NFDRS, the mean observed STL could be calculated per Grid Square, per month.	Monthly means of Observed STL
Observed Ignition Component (IC)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	Monthly means of observed IC were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the daily datasheets from the NFDRS, the mean observed IC could be calculated per Grid Square, per month.	Monthly means of Observed IC

Table A4.2 Details of the statistical techniques and analyses employed in Chapter 4 with reference to specific figure and table outputs and information on how the particular outputs from each stage of analysis should be interpreted.

Step	**Analysis Step Details**	**Specific variables used**	**Statistical Techniques used**	**Figure and Table Outputs**	**How to interpret outputs**
1	Understanding the relationship between the observed Fire Danger Indices and the metrics of fire activity across the US through the use of correlation in each grid square across the country.	Monthly-means of each Observed FDI with monthly-totals of Fire Activity, creating six correlation pairs	Spearman's Rank Correlation (per Grid Square)	Figure 4.3.	Correlation coefficient values range from -1 to 1. A negative value indicate an inverse or negative relationship between the two variables used. Positive values indicate positive relationships, as one variable increases, the other variable increases. The closer the coefficient is to -1 or 1, the stronger the positive, or negative relationship. Values near zero indicate either no relationship or a very weak relationship between the two variables. Spearman's Rank correlation was chosen as it allows for the correlation of both ordinal and continuous datasets as well as identifying non-linear relationships as it ranks values as appose to having the values unranked.
2	Quantifying and contrasting the correlation coefficients across the country produced in Step 1 of this chapter.	Monthly-means of each Observed FDI and monthly-totals of Fire Activity	Histograms of correlation coefficients from Step 1.	Figure 4.4.	Histograms show the distribution of values in the dataset examined. This can be displayed through frequency counts per value range, or as a density value where the proportion of the total sample that is represented by data in a certain value range is calculated.

3	Quantifying and contrasting the distributions of all monthly-mean values of the of each Observed FDI	Distributions of the Monthly-means values of each Observed FDI	Histograms of the Index values for the observed FDR, the observed STL, and the observed IC.	Figure 4.6.	Histograms show the distribution of values in the dataset - what are the most common, frequency counts per value range, or density where the proportion of the total sample that is represented by data in a certain value range is calculated.
4	Understanding, on the national-scale, the relationships and trends between each of the observed Fire Danger Indices with both Fire Occurrence and Final Fire Size.	Monthly-means of each Observed FDI and monthly-totals of Fire Activity	Scatter plots and percentile trends (all Grids Squares together in aggregate)	Figure 4.7.	This figure allows the reader to examine the relationships between the observed fire danger indices and fire activity across the conterminous US in aggregate. The distributions of fire activity are also displayed across the spectrums of each of the fire danger indices with the 50th, 75th, 95th, and 99th percentile value of FO and FFS across each FDI spectrum
5	Understanding, on the national-scale, the trends in both Fire Occurrence and Final Fire Size across the spectrums of the three Fire Danger Indices.	Monthly-means of each Observed FDI and monthly-totals of Fire Activity	Moving-means of Fire Activity across FDI spectrums ± 1 standard error from the mean (all Grids Squares together in aggregate)	Figure 4.8.	This technique is another means of exploring the relationships between the fire danger indices and fire activity. The mean of fire occurrence and final fire size is calculated at regular fire danger index values with the standard error indicating how representative the mean is of the distributions of fire occurrence and final fire size at that index value. A wider standard error window indicates a less representative mean value of fire activity.

Appendix V: Further details on data and methods employed in Chapter 5

Table A5.1 Details of the data utilised in Chapter 5 with information on how the data was processed and the variables created for analysis in this chapter.

Data Utilised	**Data Source**	**Original Format**	**Data Processing**	**Exploratory Variables Created**
Fire Occurrence (FO)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Monthly totals of FO were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the USFS FPA FOD, the number of fires that occurred per Grid Square, per month, could be calculated.	Monthly totals of FO
Final Fire Size (FFS, acres)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Monthly totals of FFS were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the USFS FPA FOD, the total number of acres burned from fires that occurred per Grid Square, per month, could be calculated.	Monthly totals of FFS
Forecasted Fire Danger Rating (FDR)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the forecasted weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network	Monthly and daily means of forecasted FDR were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date,	Monthly means of Forecasted FDR and Daily means of Forecasted FDR

		for that particular day. Data entries include latitudinal and longitudinal data from each weather station, forecasted weather data, and derived forecast of fire danger index values.	longitude, and latitude information from the daily datasheets from the NFDRS, the mean forecasted FDR could be calculated per Grid Square, per month and per day.	
Forecasted Staffing Level (STL)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the forecasted weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, forecasted weather data, and derived forecast of fire danger index values.	Monthly and daily means of forecasted STL were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the daily datasheets from the NFDRS, the mean forecasted STL could be calculated per Grid Square, per month and per day.	Monthly means of Forecasted STL and Daily means of Forecasted STL
Forecasted Ignition Component (IC)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the forecasted weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, forecasted weather data, and derived forecast of fire danger index values.	Monthly and daily means of forecasted IC were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the daily datasheets from the NFDRS, the mean forecasted IC could be calculated per Grid Square, per month and per day.	Monthly means of Forecasted IC and Daily means of Forecasted IC
Observed Fire Danger Rating (FDR)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network	Monthly and daily means of observed FDR were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date,	Monthly means of Observed FDR and Daily means of Observed FDR

		for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	longitude, and latitude information from the daily datasheets from the NFDRS, the mean FDR could be calculated per Grid Square, per month and per day.	
Observed Staffing Level (STL)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	Monthly and daily means of observed STL were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the daily datasheets from the NFDRS, the mean STL could be calculated per Grid Square, per month and per day.	Monthly means of Observed STL and Daily means of Observed STL
Observed Ignition Component (IC)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	Monthly and daily means of observed IC were calculated per 1x1 degree Grid Square, (96 data points per Grid Square across the study period). Using the date, longitude, and latitude information from the daily datasheets from the NFDRS, the mean IC could be calculated per Grid Square, per month and per day.	Monthly means of Observed IC and Daily means of Observed IC

Table A5.2 Details of the statistical techniques and analyses employed in Chapter 5 with reference to specific figure and table outputs and information on how the particular outputs from each stage of analysis should be interpreted.

Step	Analysis Step Details	Specific variables used	Statistical Techniques used	Figure and Table Outputs	How to interpret outputs
1	Understanding the relationship between the observed and forecasted Fire Danger Indices across the US by conducting correlations in each grid square across the country.	Daily-means of each Observed FDI and Daily-means of each Forecasted FDI, creating three correlation pairs	Spearman's Rank Correlation (per Grid Square)	Figure 5.2.	Correlation coefficient values range from -1 to 1. A negative value indicate an inverse or negative relationship between the two variables used. Positive values indicate positive relationships, as one variable increases, the other variable increases. The closer the coefficient is to -1 or 1, the stronger the positive, or negative relationship. Values near zero indicate either no relationship or a very weak relationship between the two variables. Spearman's Rank correlation was chosen as it allows for the correlation of both ordinal and continuous datasets as well as identifying non-linear relationships as it ranks values as appose to having the values unranked.
2	Quantifying and contrasting the correlation coefficients across the country produced in Step 1 of this chapter.	Daily-means of each Observed FDI and Daily-means of each Forecasted FDI	Histograms of correlation coefficients	Figure 5.3.	Histograms show the distribution of values in the dataset examined. This can be displayed through frequency counts per value range, or as a density value where the proportion of the total sample that is represented by data in a certain value range is calculated.

3	An initial appreciation of the accuracy of daily forecasts of fire danger. Plotting the observed FDI value against the forecasted value from all grid squares for every day in the study period. Plotted as a density plot with breaks across the value spectrums in order to show the frequency of occurrences of when the forecasted and observed FDIs were of specific values.	Daily-means of each Observed FDI and Daily-means of each Forecasted FDI	Heatmaps comparing forecasted vs observed FDIs	Figure 5.4.	Heatmaps indicates the frequency at which data values occur within a certain value range. Each square in the heatmap represents a certain value range across the observed and forecasted fire danger indices. The colour of each square represents the amount of times (log10) data occurs within those specific value ranges.
4	A basic understanding of the relationship between forecasted and observed FDIs and the accuracy of the forecasts in comparison with 'perfect' forecast accuracy, where forecasts equal the observed value.	Daily-means of each Observed FDI and Daily-means of each Forecasted FDI	Linear regression model	Figure 5.4.	The linear model shows the relationship between the forecasted and observed FDIs (FDR, STL, and IC). Where the linear model line is positioned relative to the y=x line infers whether, on a national scale, the forecasts over or under predict fire danger at different stages along the FDI value spectrum.
5	Understanding the relationship between the forecasted Fire Danger Indices and the metrics of fire activity across the US	Monthly-means of each Forecasted FDI and monthly-totals of Fire	Spearman's Rank Correlation (per Grid Square)	Figure 5.5.	Correlation coefficient values range from -1 to 1. A negative value indicate an inverse or negative relationship between the two variables used. Positive values indicate positive relationships, as one variable

	through the use of correlation in each grid square across the country.	Activity, 6 correlation pairs			increases, the other variable increases. The closer the coefficient is to -1 or 1, the stronger the positive, or negative relationship. Values near zero indicate either no relationship or a very weak relationship between the two variables. Spearman's Rank correlation was chosen as it allows for the correlation of both ordinal and continuous datasets as well as identifying non-linear relationships as it ranks values as appose to having the values unranked.
6	Quantifying and contrasting the correlation coefficients across the country produced in Step 5 of this chapter.	Monthly-means of each Forecasted FDI and monthly-totals of Fire Activity, 6 correlation pairs	Histograms of correlation coefficients	Figure 5.6.	Histograms show the distribution of values in the dataset examined. This can be displayed through frequency counts per value range, or as a density value where the proportion of the total sample that is represented by data in a certain value range is calculated.
7	Comparison of the relationships between fire activity and the observed FDIs and forecasted FDIs, respectively. Essentially comparing Figure 4.3 and Figure 5.5 by subtracting the correlation coefficients in every grid squares in Figure 5.5 from the respective coefficients in Figure 4.3.	Correlation coefficients from monthly-means of each Observed FDI and monthly-totals of Fire Activity and correlation coefficient from Monthly-means of each Forecasted FDI and monthly-totals of Fire Activity	Comparison of Spearman's Rank Correlation Coefficients (per Grid Square)	Figure 5.7.	Figure 5.7 displays regions with weaker relationships between the forecasted FDIs and fire activity, and observed FDIs and fire activity. Based on the calculation, the higher the magnitude the difference, the weaker the relationship between forecasted FDIs and fire activity when compared to the relationship between the observed FDIs and fie activity.

Appendix VI: Further details on data and methods employed in Chapter 6

Table A6.1 Details of the data utilised in Chapter 6 with information on how the data was processed and the variables created for analysis in this chapter.

Data Utilised	Data Source	Original Format	Data Processing	Exploratory Variables Created
Fire Occurrence (FO)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Monthly-mean variance in FO (12 data points, nationally) were calculated by firstly calculating daily totals of FO for the time period 2006-2013. These were then used to evaluate the daily variance in FO across the eight years. These daily variances were then used to compute the monthly-mean variance in FO across the eight years.	Monthly-mean variance in FO (12 data points).
Final Fire Size (FFS, acres)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Monthly-mean variance in FFS (12 data points, nationally) were calculated by firstly calculating daily totals of FFS for the time period 2006-2013. These were then used to evaluate the daily variance in FFS across the eight years. These daily variances were then used to compute the monthly-mean variance in FFS across the eight years.	Monthly-mean variance in FFS (12 data points).
Forecasted Fire Danger Rating and Observed Fire Danger Rating (FDR)	NFDRS Archive (WFAS.net/archive)	Data archive of daily NFDRS datasheets. Both observed and forecasted data were utilised in this chapter. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal	Daily means of forecasted and observed FDR values for every day in the study period, per 1 x1 Grid Square, were utilised to create subset populations of instances where the forecasted FDR values were either over-predicted, under-predicted, or correctly-predicted, when compared to the observed FDR values. These subset populations were then used to calculate the percentage of forecasts per month that were	Sub-set Populations of FDR Over-Prediction, FDR Prediction, FDR Under-Prediction, and FDR Correct-Prediction. Percentage of forecasts that were

		data from each weather station, forecasted weather data, and derived forecast of fire danger index values.	in each subset population, creating monthly percentages of FDR forecasts that were over-, under-, or correctly-predicted.	over-, under-, correctly-predicted per month (12 data points).
Forecasted Staffing Level and Observed Staffing Level (STL)	NFDRS Archive (WFAS.net/archive)	Data archive of daily NFDRS datasheets. Both observed and forecasted data were utilised in this chapter. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, forecasted weather data, and derived forecast of fire danger index values.	Daily means of forecasted and observed STL values for every day in the study period, per 1 x1 Grid Square, were utilised to create subset populations of instances where the forecasted STL values were either over-predicted, under-predicted, or correctly-predicted, when compared to the observed STL values. These subset populations were then used to calculate the percentage of forecasts per month that were in each subset population, creating monthly percentages of STL forecasts that were over-, under-, or correctly-predicted.	Sub-set Populations of STL Over-Prediction, STL Under-Prediction, and STL Correct-Prediction. Percentage of forecasts that were over-, under-, correctly-predicted per month (12 data points).
Forecasted Ignition Component and Observed Ignition Component (IC)	NFDRS Archive (WFAS.net/archive)	Data archive of daily NFDRS datasheets. Both observed and forecasted data were utilised in this chapter. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, forecasted weather data, and derived forecast of fire danger index values.	Daily means of forecasted and observed IC values for every day in the study period, per 1 x1 Grid Square, were utilised to create subset populations of instances where the forecasted IC values were either over-predicted, under-predicted, or correctly-predicted, when compared to the observed IC values. These subset populations were then used to calculate the percentage of forecasts per month that were in each subset population, creating monthly percentages of IC forecasts that were over-, under-, or correctly-predicted.	Sub-set Populations of IC Over-Prediction, IC Under-Prediction, and IC Correct-Prediction. Percentage of forecasts that were over-, under-, correctly-predicted per month (12 data points).

Table A6.2 Details of the statistical techniques and analyses employed in Chapter 6 with reference to specific figure and table outputs and information on how the particular outputs from each stage of analysis should be interpreted.

Step	**Analysis Step Details**	**Specific variables used**	**Statistical Techniques used**	**Figure and Table Outputs**	**How to interpret outputs**
1	An initial appreciation of the accuracy of daily forecasts of fire danger. Plotting the observed FDI value against the forecasted value from all grid squares for every day in the study period. Plotted as a density plot with breaks across the value spectrums in order to show the frequency of occurrences of when the forecasted and observed FDIs were of specific values.	Daily-means of each Observed FDI and Daily-means of each Forecasted FDI	Heatmaps comparing forecasted vs observed FDIs	Figure 6.1.	Heatmaps indicates the frequency at which data values occur within a certain value range. Each square in the heatmap represents a certain value range across the observed and forecasted fire danger indices. The colour of each square represents the amount of times (log10) data occurs within those specific value ranges.
2	Based on the spread of index values and the difference between forecast and observed FDIs, populations of over-, under-, and correct-prediction were created based on whether forecasts were greater than, less than, or equal to the observed FDIs. For each FDI, ± 2 Standard Deviations of the mean	Daily-means of each Observed FDI and Daily-means of each Forecasted FDI	Defining Sub-set populations of Over-, under-, and correct-prediction	Figure 6.1 and Table 6.1.	Instances where the forecasts were above the upper dashed line in Figure 6.1 were considered as over-predicted forecasts of fire danger. Instances where the forecasts were below the lower dashed line in Figure 6.1 were considered as under-predicted forecasts of fire danger. Instances where the forecasts were within the dashed

	difference between forecasted and observed values for each FDI were used as thresholds for the three sub-set populations of prediction accuracy.				lines are considered as broadly accurate or correctly-predicted forecasts of fire danger. The size of the sub-sets can be seen in able 6.1.
3	The monthly percentages of forecasting accuracy (the percentage of forecasts that were over-, under-, and correctly predicted per month) were correlated with the monthly-mean variance in Fire Occurrence and Final Fire Size in order to understand the relationship between the forecasting accuracy of the NFDRS and fire activity. This was conducted on both the national scale, all grid squares in aggregate, and for each grid square across the country on a 1x1 degree grid.	Monthly-mean percentage of 1-day forecasts in each Sub-set population of accuracy (the percentage of forecasts that were over-, under-, and correctly-predicted per month) and Monthly-mean variance in Fire Occurrence and Final Fire Size	Spearman's Rank Correlation (Nationally and per Grid Square) of percentages of accuracy per FDI and variance in Fire Activity	Figure 6.4, Figure 6.11, and Table 6.2. Figures 6.5, 6.7, 6.9, and 6.12.	Correlation coefficient values range from -1 to 1. A negative value indicate an inverse or negative relationship between the two variables used. Positive values indicate positive relationships, as one variable increases, the other variable increases. The closer the coefficient is to -1 or 1, the stronger the positive, or negative relationship. Values near zero indicate either no relationship or a very weak relationship between the two variables. Spearman's Rank correlation was chosen as it allows for the correlation of both ordinal and continuous datasets as well as identifying non-linear relationships as it ranks values as appose to having the values unranked.

4	Following Step 3, to quantify and contrast the correlation coefficients between forecasting accuracy and fire activity, histograms were produced.	Monthly-mean percentage of 1-day forecasts in each Sub-set population of accuracy and Monthly-mean variance in Fire Occurrence and Final Fire Size	Histograms of correlation coefficients	Figures 6.6, 6.8, and 6.10.	Histograms show the distribution of values in the dataset examined. This can be displayed through frequency counts per value range, or as a density value where the proportion of the total sample that is represented by data in a certain value range is calculated.

Appendix VII: Further details on data and methods employed in Chapter 7

Table A7.1 Details of the data utilised in Chapter 7 with information on how the data was processed and the variables created for analysis in this chapter.

Data Utilised	Data Source	Original Format	Data Processing	Exploratory Variables Created
Observed Fire Danger Rating (FDR)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	Daily means of FDR per 1x1 Grid Square, (2922 data points per Grid Square across the study period). For every grid square, using latitudinal and longitudinal data, FDR data was associated for every day that each fire that occurred in the grid square burned for, using the dates of discover and containment. Using this daily record of FDR values per fire, the mean and standard deviation in FDR values per fire were then calculated to statistically summaries the FDR conditions for each individual fire. The distributions of FDR conditions for individual fires (mean and SD) were normalised by range per Fire Size Class for percentile analysis and Principal Component Analysis.	FE_FDR_mean and FE_FDR_SD (the mean and standard deviation of observed FDR values during each individual fire per Fire Size Class)
Observed Staffing Level (STL)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day.	Daily means of STL per 1x1 Grid Square, (2922 data points per Grid Square across the study period). For every grid square, using latitudinal and longitudinal data, STL data was associated for every day that each fire that occurred in the grid square burned for, using the dates of discover and containment. Using this daily record of STL values per fire, the mean and standard	FE_STL_mean and FE_STL_SD (the mean and standard deviation of observed STL values during each individual fire per Fire Size Class)

		Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	deviation in STL values per fire were then calculated to statistically summaries the STL conditions for each individual fire. The distributions of STL conditions for individual fires (mean and SD) were normalised by range per Fire Size Class for percentile analysis and Principal Component Analysis.	
Observed Ignition Component (IC)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	Daily means of IC per 1x1 Grid Square, (2922 data points per Grid Square across the study period). For every grid square, using latitudinal and longitudinal data, IC data was associated for every day that each fire that occurred in the grid square burned for, using the dates of discover and containment. Using this daily record of IC values per fire, the mean and standard deviation in IC values per fire were then calculated to statistically summaries the IC conditions for each individual fire. The distributions of IC conditions for individual fires (mean and SD) were normalised by range per Fire Size Class for percentile analysis and Principal Component Analysis.	FE_IC_mean and FE_IC_SD (the mean and standard deviation of observed IC values during each individual fire per Fire Size Class)
Observed Spread Component (SC)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting	Daily means of SC per 1x1 Grid Square, (2922 data points per Grid Square across the study period). For every grid square, using latitudinal and longitudinal data, SC data was associated for every day that each fire that occurred in the grid square burned for, using the dates of discover and	FE_SC_mean and FE_SC_SD (the mean and standard deviation of observed SC values during each individual fire per Fire Size Class)

		weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	containment. Using this daily record of SC values per fire, the mean and standard deviation in SC values per fire were then calculated to statistically summaries the SC conditions for each individual fire. The distributions of SC conditions for individual fires (mean and SD) were normalised by range per Fire Size Class for percentile analysis and Principal Component Analysis.	
Observed Burning Index (BI)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	Daily means of BI per 1x1 Grid Square, (2922 data points per Grid Square across the study period). For every grid square, using latitudinal and longitudinal data, BI data was associated for every day that each fire that occurred in the grid square burned for, using the dates of discover and containment. Using this daily record of BI values per fire, the mean and standard deviation in BI values per fire were then calculated to statistically summaries the BI conditions for each individual fire. The distributions of BI conditions for individual fires (mean and SD) were normalised by range per Fire Size Class for percentile analysis and Principal Component Analysis.	FE_BI_mean and FE_BI_SD (the mean and standard deviation of observed BI values during each individual fire per Fire Size Class)
Observed Energy Release Component (ERC)	NFDRS Archive (WFAS.net/ archive)	Data archive of daily NFDRS datasheets. This datasheet details the observed weather and fire danger conditions. Each daily .txt file is	Daily means of ERC per 1x1 Grid Square, (2922 data points per Grid Square across the study period). For every grid square, using latitudinal and longitudinal data, ERC data was associated for every day that each	FE_ERC_mean and FE_ERC_SD (the mean and standard deviation of observed ERC values during

		unformatted but each row identifies each reporting weather station in the RAWS network for that particular day. Data entries include latitudinal and longitudinal data from each weather station, observed weather data, and derived fire danger index values.	fire that occurred in the grid square burned for, using the dates of discover and containment. Using this daily record of ERC values per fire, the mean and standard deviation in ERC values per fire were then calculated to statistically summaries the ERC conditions for each individual fire. The distributions of ERC conditions for individual fires (mean and SD) were normalised by range per Fire Size Class for percentile analysis and Principal Component Analysis.	each individual fire per Fire Size Class)
Fire Size Class (A-G)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Fire Size Classes as defined by the National Wildfire Coordinating Group were used to categorise the recorded fire events using their final fire size and each class' size boundary thresholds.	FSC (A-G)
Burning Duration (days)	USFS FPA FOD (Short, 2014)	Database with longitude and latitudinal point data in table form. Each row represents an individual fire, detailing the start and end dates of the fire, its final size, and final fire class data.	Number of days each fire burned for, determined by using the Date of Containment (DOC) - Date of Discovery (DOD). The distributions of Burning Duration (BD) for individual fires were normalised by range per Fire Size Class for percentile analysis and Principal Component Analysis.	BD (days)

Table A7.2 Details of the statistical techniques and analyses employed in Chapter 7 with reference to specific figure and table outputs and information on how the particular outputs from each stage of analysis should be interpreted.

Step	Analysis Step Details	Specific variables used	Statistical Techniques used	Figure and Table Outputs	How to interpret outputs
1	Once the exploratory variables were created, details in Table 7.1, boxplots were produced for each variable for the seven Fire Size Classes in order to compare their distributions.	Burning Duration, Fire Event Means for each FDI, Fire Event Standard Deviations of each FDI per Fire Size Class	Percentile boxplots of normalised exploratory variables per Fire Size Class	Figures 7.2. - 7.6.	Boxplots allow the reader to interpret the distribution of values based on percentile breakpoints. Shorter boxes suggest that the range of values is very small, whilst longer boxes indicate wider ranges of values in the dataset. Boxes that higher than one another indicate the different value magnitudes. As the boxplots exhibited here utilised normalised data, the different plots can be compared and contrasted.
2	To further compare the distributions of variables across the Fire Size Classes, Wilcoxon significant difference Tests and Kolmogorov Smirnov tests were conducted to determine significant difference between distributions of variables between Fire Size Classes	Burning Duration, Fire Event Means for each FDI, Fire Event Standard Deviations of each FDI per Fire Size Class	Wilcoxon significant difference tests and Kolmogorov Smirnov tests per Fire Size Class for each exploratory variable.	Table 7.3.	The Wilcoxon tests is used to determine whether two sample datasets are from the same population. The null hypothesis is that the two samples are from the same population, so finding a p value less than or equal to 0.05 would indicate that the two samples are significantly different from one another. The 2-sample Kolmogorov-Smirnov test determines whether two datasets differ significantly from one-another and provides both a D statistic and a P value. The null hypothesis is that the two datasets are the same. The D statistic indicates the magnitude of difference between the cumulative distributions of the two datasets being tested, whilst the p value indicates whether the datasets differ significantly, therefore a $p>0.05$ allows for the null hypothesis to be rejected.

3	Following on from the percentile analysis, certain variables, listed here, were retained for Principal Component Analysis in order to evaluate the relative importance of the remaining variables in determining the variance in each Fire Size Class. The outputs were then compared between the Fire Size Classes in order to see what different combinations of variables determined the majority of variance in each Fire Size Class.	Burning Duration, Fire Event Standard Deviations of FDR, STL, IC, and ERC per Fire Size Class	Principal Component Analysis	Figure 7.7 and Table 7.4.	Principal Component Analysis allows the reader to understand variance in datasets and understand the internal structure of data. Orthogonal transformations are used to convert sets of observations into linearly uncorrelated variables referred to principal components. Principal components are made of the original variables of the dataset and are used to account for as much variability in the dataset as possible. 80% of the dataset's variance needs to be explained by the principal components for descriptive purposes. The outputs from this analysis that are presented in this thesis include a table of the component coefficients for each principal component per Fire Size Class and the corresponding bi-plots. The component coefficients indicate the importance of each variable in defining each of the principal components. The magnitude of the absolute value of the coefficient signifies its importance (higher the value, the more significant it is), and the direction of the direction of each coefficient (positive or negative) indicates whether the coefficients are positively or inversely associated to the principal component. The bi-plots overlay component scores (points) with the loading scores (arrows) for each variable in the two components displayed in the plot. This indicates how the data points group together and what variables drive variability in each of the Fire Size Classes.

4	Following on from the percentile analysis, certain variables, listed here, were retained for Principal Component Analysis in order to evaluate the relative importance of the remaining variables in determining the variance in each Fire Size Class. The outputs were then compared between the Fire Size Classes in order to see what different combinations of variables determined the majority of variance in each Fire Size Class.	Fire Event Standard Deviations of FDR, STL, IC, and ERC per Fire Size Class	Principal Component Analysis	Figure 7.8 and Table 7.5.	Principal Component Analysis allows the reader to understand variance in datasets and understand the internal structure of data. Orthogonal transformations are used to convert sets of observations into linearly uncorrelated variables referred to principal components. Principal components are made of the original variables of the dataset and are used to account for as much variability in the dataset as possible. 80% of the dataset's variance needs to be explained by the principal components for descriptive purposes. The outputs from this analysis that are presented in this thesis include a table of the component coefficients for each principal component per Fire Size Class and the corresponding bi-plots. The component coefficients indicate the importance of each variable in defining each of the principal components. The magnitude of the absolute value of the coefficient signifies its importance (higher the value, the more significant it is), and the direction of the direction of each coefficient (positive or negative) indicates whether the coefficients are positively or inversely associated to the principal component. The bi-plots overlay component scores (points) with the loading scores (arrows) for each variable in the two components displayed in the plot. This indicates how the data points group together and what variables drive variability in each of the Fire Size Classes.

“Things were better in my day”

Geoffrey Boycott

References:

Abatzoglou JT, Williams AP. (2016) Impact of anthropogenic climate change on wildfire across the western US forests. *Proceedings of the National Academy of Sciences*, 113(42), 11770-11775. doi: 10.1073/pnas.1607171113

Agee JK. (1993) Fire Ecology of Pacific Northwest Forests. Island Press. Washington, D.C.

Albini, FA (1976) Estimating wildfire behavior and effects. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-30, 92 pp.

Albini FA. (1982) Response of free-burning fire to non-steady wind. *Combustion Science and Technology*, 29, 225–41.

Alexander ME, Cruz MG (2011) Interdependencies between flame length and fireline intensity in predicting crown fire initiation and crown scorch height. *International Journal of Wildland Fire*, 21, 95–113; doi: org/10.1071/WF11001.

Alexander ME, Cruz MG (2013) Limitations on the accuracy of model predictions of wildland fire behaviour: A state-of-the-knowledge overview. *The Forestry Chronicle*, 89(3), 372-383.

Alonso-Canas I, Chuvieco E. (2015) Global burned area mapping from ENVISAT -MERIS and MODIS active fire data, *Remote Sensing of Environment*, 163, 140-152.

Andrews PL, Bradshaw LS (1997) FIRES: Fire Information Retrieval and Evaluation System – a program for fire danger rating analysis. USDA Forest Service, Intermountain Research Station, General Technical Report INT-GTR-367. (Ogden, UT, USA).

Andrews PL, Loftsgaarden DO, Bradshaw LS (2003) Evaluation of fire danger rating indexes using logistic regression and percentile analysis. *International Journal of Wildland Fire*, 12, 213–226. doi:10.1071/ WF02059

Arienti MC, Cumming S, Boutin S. (2006) Empirical models of forest fire initial attack success probabilities: the effects of fuels, anthropogenic linear features, fire weather, and management, *Canadian Journal of Forest Research*, 36, 3155-3166.

Arizona State Forester (2013) Yarnell Hill Fire Serious Accident Investigation Report. Available at: https://docs.google.com/file/d/0B36DIycSgbzWSUtjNkl1Z2ROT0k/edit [verified 23 April 2018].

Arpaci A, Eastaugh CS, Vacik H (2013) Selecting the best performing fire weather indices for Austrian ecoregions. *Theoretical and Applied Climatology*, 114, 393–406. doi:10.1007/S00704-013-0839-7

Barbero R, Abatzoglou JT, Steel EA, Larkin NK (2014) Modelling very large-fire occurrences over the continental United States from weather and climate forcing. *Environmental Research Letters*, 9, 124009. doi:10.1088/1748-9326/9/12/124009

Barbero R, Abatzoglou JT, Kolden C, Hegewisch K, Larkin NK, Podschwit H (2015) Multi-scalar influence of weather and climate on very large-fires in the eastern United States. *International Journal of Climatology*, 35, 2180–2186. doi:10.1002/JOC.4090

Barnes, L.R., Gruntfest E.C., Hayden M.H., Schultz D.M., Benight C (2007) False Alarms and Close Calls: A Conceptual Model of Warning Accuracy. *Weather Forecasting*, 22, 1140–1147, https://doi.org/10.1175/WAF1031.1

Beck JA, Alexander ME, Harvey SD, Beaver AK (2002) Forecasting diurnal variations in fire intensity to enhance wildland firefighter safety, *International Journal of Wildland Fire*, 11, 173-182.

Beer T. (1991) The interaction of wind and fire. *Boundary Layer Meteorology*, 54, 287–308.

Belcher, C. M., Yearsley, J. M., Hadden, R. M., McElwain, J. C., & Rein, G. (2010). Baseline intrinsic flammability of Earth’s ecosystems estimated from paleoatmospheric oxygen over the past 350 million years. *Proceedings of the National Academy of Sciences*, 107(52), 22448-22453.

Belcher CM, Collinson ME, Scott AC. (2013) A 450-Million-Year History of Fire. In Fire Phenomena and the Earth System, C. M. Belcher (Ed.). doi:10.1002/9781118529539.ch12

Benson RP, Roads JO, Weise DR. (2009) Climatic and weather factors affecting fire occurrence and behavior. In Bytenerowicz A, Arbaugh M, Riebau A, Andersen C. (eds) Developments in Environmental Science, vol. 8. Elsevier B.V., pp. 37–59.

Bond WJ, and Keeley JE. (2005) Fire as a global 'herbivore': the ecology and evolution of flammable ecosystems. *Trends in Ecology and Evolution*. 20: 387-394.

Bowman DMJS, Balch JK, Artaxo P, Bond WJ, Carlson JM, Cochrane MA, D'antonio CM, DeFries RS, Doyle JC, Harrison SP, Johnstone FH, Keeley JE, Krawchuk MA, Kull CA, Martson, JB, Moritz, MA, Prentice IC, Roos CI, Scott AC, Swetnam TW, van der Werf GR, Pyne SJ, (2009) Fire in the Earth System. *Science*, 324:481-484

Bradshaw LS, Deeming JE, Burgan RE, Cohen JD (1983) The 1978 National Fire-Danger-Rating System: technical documentation. USDA Forest Service, Intermountain Forest and Range Experiment Station General Technical Report INT-169. (Ogden, UT)

Brain, JR. (2000) NFDRS Indices—Why are they so high? One possible answer. Available at https://fam.nwcg.gov/fam-web/helpdesk/reports/jb_nfdrs_Outputs.rtf [verified 15 May 2018]

Breznitz S. (1984) The false alarm effect. Cry Wolf: The Psychology of False Alarms, Lawrence Erlbaum Associates, 9–16.

Brown TJ, Hall BL, Westerling AL, (2004) The Impact of Twenty-First Century Climate Change on Wildland Fire Danger in the Western United Stated: An Applications Perspective. *Climatic Change*, 62, 365–388.

Burgan RE (1979) Estimating live fuel moisture for the 1978 National Fire-Danger-Rating System – 1978. USDA Forest Service, Intermountain Forest and Range Experiment Station Research Paper INT-226. (Ogden, UT)

Burgan RE (1988) 1988 Revisions to the 1978 Fire danger Rating System. USDA Forest Service, Southeastern Forest Station Research Paper SE273. (Asheville, CN, USA)

Burgan RE (1993) A method to initialize the Keet-Byram Drought Index, *Western Journal of Applied Forestry*, 8(4), 109-115.

Butler BW, Barthlette RA, Bradshaw LS, Cohen JD, Andrews PL, Putnam T, Mangan RJ. (1998) Fire Behaviour Associated with the 1994 South Canyon Fire on Storm King Mountain, Colorado. USDA Forest Service, Rocky Mountain Research Station, Research Paper RMRS-RP-9. (Ogden, Utah, USA)

Butry DT, Gumpertz M, Genton MG. ed., (2008) The production of Large and Small Wildfires. In: The Economics of Forest Disturbances: Wildfires Storms and Invasive Species. Springer Science, p.79-106.

Byrant, B.P., Westerling, A.L. (2014) Scenarios for future wildfire risk in California: links between changing demography, land use, climate, and wildfire. *Environmetrics*, 25(6), 454-471.

Calkin DE, Gebert KM, Jones JG, Neilson RP (2005) Forest Service Large Fire Area Burned and Suppression Expenditure Trends, 1970–2002. *Journal of Forestry*, 103, 179–183.

Calkin DE, Thompson MP, Finney MA. (2015) Negative consequences of positive feedbacks in US wildfire management. *Forested Ecosystems*, 2: 9. https://doi.org/10.1186/s40663-015-0033-8

Carlson, J.D., Bradshaw L.S., Nelson Jr. R.M., Jabrzemski R., (2005a). Evaluation of the Nelson dead fuel moisture model in a forecast environment. Conference CD, Sixth Symposium on Fire and Forest Meteorology, American Meteorological Society, Oct. 25- 27, Canmore, AB, Paper 7.3, 14 pp

Carlson, J.D., Bradshaw L.S, Nelson Jr. R.M., Bensch R.R., Jabrzemski R., (2005b). Field verification of the Nelson dead fuel moisture model and comparisons with National Fire Danger Rating System (NFDRS) predictions. Conference CD, Sixth Symposium on Fire and Forest Meteorology, American Meteorological Society, Oct. 25-27, Canmore, AB, Paper P1.5

Carlson, J.D., Bradshaw L.S., Nelson Jr. R.M, Bensch R.R., and Jabrzemski R. (2007). Application of the Nelson model to four timelag fuel classes using Oklahoma field observations: model evaluation and comparison with National Fire Danger Rating System algorithms. *International Journal of Wildland Fire*, 16. 10.1071/WF06073.

Cohen JD, Deeming JE (1985) The National Fire Danger Rating System: Basic equations. USDA Forest Service, Pacific Southwest Forest and Range Experiment Station, General Technical Report PSW-82. (Berkeley, CA, USA)

Corelogic, Botts, H, Jeffery, T., Kolk, S., McCabe, S., Stueck, B., Suhr, L. (2013) Wildfire Hazard Risk Report

Countryman CM (1972) The fire environment concept. Berkeley, CA: USDA Forest Service, Pacific Southwest Forest and Range Experiment Station. 15 p.

Countryman CM (1996) The concept of fire environment, *Fire Control Notes*, 27(4), 8-10.

Cruz MG, Alexander ME, (2010) Assessing crownfire potential in coniferous forests of western North America: a critique of current approaches and recent simulation studies. *International Journal of Wildland Fire*, 19, 377–98.

Cruz MG, Alexander ME (2013) Uncertainty associated with model predictions of surface and crown fire rates of spread. *Environmental Modelling & Software*, 47, 16-18.

Dai, A. (2013) Increasing drought under global warming in observations and models. *Nature Climate Change*, 3, 52–58.

Deeming JE, Lancaster JW, Fosberg MA, Furman RW, Schroeder P (1972) National Fire-Danger-Rating System. USDA Forest Service, Rocky Mountain Forest and Range Experiment Station, Research Paper RM-84.

Deeming JE, Burgan RE, Cohen JD (1977) The National Fire-Danger Rating System – 1978. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-39. (Fort Collins, CO, USA)

Dennison, P.E., Brewer, S.C., Arnold, J.D., Moritz, M.A. (2014) Large wildfire trends in the western United States, 1984-2011. *Geophysical Research Letters*, 41, 2928-2933

Dessler, A. E., Zhang, Z., Yang, P. (2008) Water-vapour climate feedback inferred from climate fluctuations, 2003–2008. *Geophysical Research Letters*, 35, L20704

Dewhirst RA, Belcher CMB. (*in review*) Pine species that support crown fire regimes have lower leaf-level terpene contents to support the success of reproduction via serotiny. *Nature Plants*.

Donnegan JA, Veblen TT, Sibold JS. (2001) Climatic and human influences on fire history in Pike National Forest, central Colorado. *Canadian Journal of Forest Research*, 31, 1526-1539.

Douglas J, Mills TJ, Artly D, Ashe D, Bartuska LA, Black R, Coloff S, Cruz J, Edrington M, Edwardson J, Gale RT, Goodman SW, Hamilton L, Landis R, Powell B, Robinson S, Schuster RJ, Stahlschmidt PK, Stires J, van Wagtendonk J, (2001). Review and Update of the 1995 Federal Wildland Fire Management Policy. U.S. Department of Agriculture and U.S. Department of the Interior.

Dow, K., Cutter S.L. (1998) Cry wolf: Repeat response to hurricane evacuation orders, *Coastal Management*, 26, 237–252.

Finney MA, Seli RC, McHugh CW, Ager AA, Bernhard B, Agee J. (2007). Simulation of long-term landscape-level fuel treatment effects on large wildfires. *International Journal of Wildland Fire*. 16. 712-727. 10.1071/WF06064.

Finney MA, McHugh CW, Grenfell IC, Riley KL, Short KC, (2011) A simulation of probabilistic wildfire risk components for the continental United States, *Stochastic Environmental Research Risk Assessment*, 25, 937-1000.

Flannigan M, Krawchuk MA, de Groot WJ, Wotton BM, Gowman LM. (2009) Implications of changing climate for global wildland fire, *International Journal of Wildland Fire*, 18, 483–507. (doi:10.1071/WF08187)

Flannigan M, Cantin AS, de Groot WJ, Wotton M, Newbery A, Gowman LM. (2013). Global wildland fire season severity in the 21st Century. *Forest Ecology and Management*, 294, 54-61.

Fosberg, M.A., Deeming, J.E. (1971) Deviation of the 1- and 10-h timelag fuel moisture calculations for fire-danger rating. Research Note RM-207. USDA Forest Service Intermountain Forest and Range Experiment Station, p. 8.

Fosberg MA, Furman RW (1971) Fire climate and fire-danger rating areas. USDS Forest Service, Rocky Mountain Forest and Range Experiment Station, Office Report 2106-6. (Fort Collins, CO, USA).

Freeborn PH, Cochrane MA, Jolly WM (2015) Relationships between fire danger and the daily number and daily growth of active incidents burning 20 in the northern Rocky Mountains, USA. *International Journal of Wildland Fire,* 24, 900–910.

Gale RS, Eubanks R, Roussopoulos PJ (1986) ‘NFDRS-East Workshop Proceedings. USDA Forest Service, Fire and Atmospheric Sciences Research. Washington, DC NFDRS-East Workshop.’ (Harper’s Ferry: WV)

Giglio L, Randerson JT, van der Werf GR. (2013) Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4), *Journal of Geophysical Research: Biosciences*, 118, 317–328, doi:10.1002/jgrg.20042.

Glasspool, IJ, Edwards D, Axe L. (2004) Charcoal in the Silurian as evidence for the earliest wildfire. *Geology*, 32, 381-383.

Graham RT, McCaffrey S, Jain TB. (tech. eds.) (2004). Science basis for changing forest structure to modify wildfire behavior and severity. Gen. Tech. Rep. RMRS-GTR-120. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 43 p.

Gude, P.H., Rasker, R., van den Noort, J. (2008) Potential for Future Development on Fire-Prone Lands. *Journal of Forestry*, 106(4), 198-205.

Gude, P.H., Jones, K., Rasker, R., Greenwood, M.C. (2013) Evidence for the effect of homes in wildfire suppression costs. *International Journal of Wildland Fire*, 22, 537-548.

Haines, D. A. (1988) A lower atmosphere severity index for wildland fires. *National Weather Digest*, 13, 23–27.

Hammer, R.B., Stewart, S.I., Radeloff, V.C. (2009) Demographic Trends, the Wildland-Urban Interface, and Wildfire Management. *Society and Natural Resources: An International Journal*, 22(8), 777-782.

Hansen, J., Ruedy, R., Sato, M., Lo, K. (2010) Global surface temperature change. *Reviews of Geophysics*, 48(4).

Hardy CE (1958) The proposed national fire danger rating system. In '1958 National Meeting of the American Meteorology Society, Logan, UT'. (American Meteorology Society:Washington, DC)

Hardy CC, Hardy CE (2007) Fire danger rating in the United States of America: an evolution since 1916. *International Journal of Wildland Fire*, 16, 217–231. doi:10.1071/WF06076

Harvey BJ. (2016) Human-caused climate change is now a key driver of forest fire activity in the western United States. *Proceedings of the National Academy of Sciences*, 201612926; DOI: 10.1073/pnas.1612926113

Holden ZA, Jolly, WM. (2011) Modelling topographic influences on fuel moisture and fire danger in complex terrain to improve wildland fire management decision support. *Forest Ecology and Management*, 262, 2133-2141.

Holmes TP, Huggett Jr. RJ, Westerling AL. ed., (2008) Statistical Analysis of Large Wildfires. In: The Economics of Forest Disturbances: Wildfires Storms and Invasive Species. Springer Science, p.59-77.

Insurance Information Institute (2015) Wildfires, [Online], Available: http://www.iii.org/issue-update/wildfires [15 May 2018]

Jolly WM, Nemani R, Running SW, (2005) A generalized, bioclimatic index to predict foliar phenology in response to climate, *Global Change Biology*, 11, 619-632.

Jolly WM, Cochrane MA, Freeborn PH, Holden ZA, Brown TJ, Williamson GJ, Bowman DMJS (2015a) Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*, 6, art7537. doi:10.1038/NCOMMS8537

Jolly WM, Bradshaw L, Wallace J. (2015b) Updating the National Fire Danger Rating System: NFDRS2016. National Predictive Services Meeting, Portland, OR.

Keeley, J.E. and Rundel, P.W. (2005) Fire and the Miocene expansion of C4 grasslands. *Ecology Letters*, 8, 683-690

Keetch JJ, Byram GM (1968) A drought index for forest fire control. USDA Forest Service, Southeastern Forest Experiment Station Research Paper SE-38. (Asheville, NC)

Krawchuk MA, Moritz MA. (2011) Constraints on global fire activity vary across a resource gradient, *Ecology*, 92, 121–132. (doi:10.1890/09-1843.1)

Lenton TM. (2011) Early warning of climate tipping points, *Nature Climate Change*, 1:201–209.

Littell JS, McKenzie D, Peterson DL, Westerling AL. (2009) Climate and wildfire area burned in western U.S. ecoprovinces, 1916-2003. *Ecological Applications*, 19(4), 1003-1021.

Liu, Y., Stanturf, J., Goodrick, S. (2010) Trends in global wildfire potential in a changing climate. *Forest Ecology and Management*, 259, 685-697.

Liu, Y., Goodrick, S., Stanturf, J. (2013) Future U.S. wildfire potential trends projected using a dynamically downscaled climate change scenario, *Forest Ecology and Management*, 294, 120-135.

Lloyd's. (2013) Wildfire: A burning Issue for Insurers? Available at: https://www.lloyds.com/news-and-risk-insight/risk-reports/library/natural-environment/wildfire-report [15 May 2018]

Luo, L., Tang, Y., Zhong, S., Bian, X., Heilman, W.E. (2013) Will Future Climate Favour More Erratic Wildfires in the Western United States? *Journal of Applied Meteorological and Climatology*, 52, 2410-2417.

Marlon JR, Bartlein PJ, Gavin DG, Long CJ, Anderson RS, Briles CE, Brown KJ, Colombaroli D, Hallett DJ, Power MJ, Scharf EA, Walsh MK. (2012) Long-term perspective on wildfires in the western USA. *Proceedings of the National Academy of Sciences*, E535–E543.

Meyn A, White PS, Buhk C, Jentsch A. (2007) Environmental drivers of large wildfires: the emerging conceptual model, *Progress in Physical Geography*, 31(3), 287-312.

Miller JD, Safford HD, Crimmins M, Thode AE. (2009) Quantitative Evidence for Increasing Forest Fire Severity in the Sierra Nevada and Southern Cascade Mountains, California and Nevada, USA. *Ecosystems*, 12, 16-22.

National Interagency Fire Center (NIFC), (2018a) Statistics. Available at https://www.nifc.gov/fireInfo/fireInfo_statistics.html [verified 13 May 2018]

National Interagency Fire Center (2018b) Federal Firefighting Costs (Suppression Only). Available at https://www.nifc.gov/fireInfo/fireInfo_documents/SuppCosts.pdf [verified 23 April 2018].

National Weather Service (2017) Fire Weather Services Product Specification. Products and Services to Support Fire and Other Incidents, NWSPD 10-4. Available at http://www.nws.noaa.gov/directives/sym/pd01004001curr.pdf [verified 19 February 2018].

National Wildfire Coordinating Group (2011a) Working with station information. In 'Weather Information Management System user's guide'. (National Wildfire Coordinating Group: Boise, ID, USA)

National Wildfire Coordinating Group (2011b) Appendix E – NFDRS technical reference. In 'Weather Information Management System user's guide'. (National Wildfire Coordinating Group: Boise, ID, USA)

National Wildfire Coordinating Group (2018) Glossary A-Z. Available at https://www.nwcg.gov/glossary/a-z [verified 23 April 2018].

Nelson RM (2000) Prediction of diurnal change in 10-h fuel stick moisture content. *Canadian Journal of Forest Research*, 30, 1071–1087. doi:10.1139/CJFR-30-7-1071

Nelson RM, Butler BW, Weise DR. (2011) Entrainment regimes and flame characteristics of wildland fires. *International Journal of Wildland Fire*, 21, 127–40.

North M. P., Stephens S. L., Collins B. M., Agee J. K., Aplet G., Franklin J. F., Fulé P. Z. (2015) Reform forest fire management, *Science*, 349 (6254), 1280-1281. DOI: 10.1126/science.aab2356

Pausas JG, Bradstock RA, Keith DA, Keeley JE, and the GCTE Fire Network, (2004) Plant functional traits in relation to fire in crown-fire ecosystems, *Ecology*, 85(4), 1085-1100

Pausas JG, Keeley JE. (2009). A burning story: the role of fire in the history of life. *Bioscience*, 59, 593–601.

Planas E, Pastor E. (2013) Wildfire Behaviour and Danger Ratings. In Fire Phenomena and the Earth System, C. M. Belcher (Ed.). doi:10.1002/9781118529539.ch4

Podur J, Wotton BM (2011) Defining fire spread event days for fire growth modelling. *International Journal of Wildland Fire*, 20, 497– 507. doi:10.1071/WF09001

Preisler HK, Brillinger DR, Burgan RE, Benoit JW (2004) Probability based models for estimation of wildfire risk. *International Journal of Wildland Fire,* 13, 133–142. doi:10.1071/WF02061

Preisler HK, Westerling AL, (2006) Statistical Model for Forecasting Monthly Large Wildfire Events in the Western United States. *Journal of Applied Meteorology and Climatology*, 46, 1020-1030

Preisler HK, Chen S, Fujioka F, Benoit JW, Westerling AL (2008) Wildland fire probabilities estimated from weather model-deduced monthly mean fire danger indices. *International Journal of Wildland Fire*, 17, 305–316. doi:10.1071/WF06162

Preisler HK, Burgan RE, Eidenshink JC, Klaver JM, Klaver RW (2009) Forecasting distributions of large Federal-lands fires utilizing satellite and gridded weather information. *International Journal of Wildland Fire*, 18, 508–516. doi:10.1071/WF08032

Pyne SJ, Andrews PL, Laven RD. (1996) Introduction to Wildland Fire, 2nd edn. John Wiley & Sons, Inc., New York.

Pyne, S. (2008) Passing the Torch, why the Eons-Old Truce Between Humans and Fire has Burst into the Age of Megafires, and what can be done about it. The American Scholar (Spring), Phi Beta Kappa Society, Washington DC. Available at https://theamericanscholar.org/passing-the-torch [verified 23 April 2018].

Qi Y, Dennison PE, Spencer J, Riaño D. (2012) Monitoring Live Fuel Moisture Using SOIL Moisture and Remote Sensing Proxies, *Fire Ecology*, 8(3), 71-87. doi:10.4996/fireecology.0803071

Radeloff, V.C., Hammer, R.B., Stewart, S.I., Fried, J.S., Holcomb, S.S., McKeefry, J.F. (2005) The Wildland-Urban Interface in the United States. *Ecological Applications*, 15:799–805.

Rehfeldt GE, Crookston NL, Sáenz-Romero C, Campbell EM. (2012) North American vegetation model for land-use planning in a changing climate: a solution to large classification problems. *Ecological Applications*, 22(1), 119-141.

Riley KL, Abatzoglou JT, Grenfell IC, Klene AE, Heinsch FA (2013) The relationship of large fire occurrence with drought and fire danger indices in the western USA, 1984–2008: the role of temporal scale. *International Journal of Wildland Fire*, 22, 894–909. doi:10.1071/WF12149

Roads J, Fujioka F, Chen S, Burgan R. (2005) Seasonal fire danger forecasts for the USA, *International Journal of Wildland Fire*, 14: 1-18.

Roads J, Tripp P, Juang H, Wang J, Fujioka F, Chen S (2010) NCEP-ECPC monthly and seasonal US fire danger forecasts. *International Journal of Wildland Fire*, 19, 399–414. doi:10.1071/WF07079

Rothermel RC (1972) A mathematical model for predicting fire spread in wildland fuels. U.S Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT. Research Paper INT-115. 40p.

Rothermel RC (1980) Fire Behaviour systems or fire management. In: Martins RE, Edmonds DA, Harrington JB, Fuquay DM, Stocks BJ, Barr S (eds.), Proceedings of the sixth conference on fire and forest meteorology, pp. 58-64. Society of American Foresters, Washington D.C.

Rothermel RC, Mutch RW (1986) Behaviour of the life-threatening Butte Fire: August 27-29, 1985, *Fire Management Notes*, 47(2), 14-24.

Routley JG. (1991) The East Bays Hills Fire, Oakland-Berkeley, California. US. Fire Administration, Technical Report Series, USFA-TR-060.

Schlobohm P, Brain, J (2002) Gaining an understanding of the National Fire Danger Rating System. National Wildfire Coordinating Group, PMS 932, NFES 2665. Available at https://www.nwcg.gov/sites/default/files/products/pms932.pdf [Verified 18 January 2018]

Schoennagel T, Veblen TT, Romme WH. (2004) The Interaction of Fire, Fuels, and Climate across the Rocky Mountain Forests. BioScience, 54(7), 661-676.

Schroeder M, Buck C. (1970) Fire weather: a guide for application of meteorological information to forest fire control operations. USDA Forest Service, Agriculture Handbook 360.

Schroeder MJ, Buck CC (1970) Fire weather…a guide for application of meteorological information to forest fire control operations U.S. Department of Agriculture, Agriculture Handbook 360. 229 pp. Washington, DC.

Scott AC, Bowman DM, Bond WJ, Pyne SJ, Alexander ME (2014) Fire on Earth: An Introduction. West Sussex, UK: Jon Wiley & Sons.
Service, Rocky Mountain Forest and Range Experiment Station, Office Report 2106-6. (Fort Collins, CO, USA)

Sharples JJ. (2008) Review of formal methodologies for wind-slope correction of wildfire rate of spread. *International Journal of Wildland Fire*, 17, 179–93.

Short KC. (2014) A spatial database of wildfires in the United States, 1992–2011, *Earth System Science Data*, 6, 1–27. doi:10.5194/ESSD-6-1-2014

Short KC. (2015a) Spatial wildfire occurrence data for the United States, 1992–2013 [FPA_FOD_20150323]. 3rd Edition. (Forest Service Research Data Archive: Fort Collins, CO, USA) doi:10.2737/RDS2013-0009.3

Short KC (2015b) Sources and implications of bias and uncertainty in a century of US wildfire activity data. *International Journal of Wildland Fire*, 24, 883–891.

Short KC. (2017) Spatial wildfire occurrence data for the United States, 1992-2015 [FPA_FOD_20170508]. 4th Edition. Fort Collins, CO: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2013-0009.4

Spracklen, D.V., Mickley, L.J., Logan, J.A., Hudman, R.C., Yevich, R., Flannigan, M.D., Westerling, A.L. (2009) Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States. *Journal of Geophysical Research*, 114.

Stavros, E.N., Abatzoglou, J.T., Larkin, N.K., McKenzie, D., Steel, E.A. (2014) Climate and very large wildland fires in the contiguous western USA. *International Journal of Wildland Fire*, 23(7), 899–914.

Stephens SL, Ruth LW. (2005) Federal Forest-Fire Policy in the United States, *Ecological Applications*, 15(2), 532-542.

Stephens SL, Agee JK, Fulé PZ, North MP, Romme WH, Swetnam TW, Turner MG. (2013) Managing forests and fire in changing climates. *Science*, 342, 41–42.

Stewart, S.I., Radeloff, V.C., Hammer, R.B., Hawbaker, T.J. (2007) Defining the Wildland-Urban Interface. *Journal of Forestry*. 105(4), 201-207.

Strategic Issues Panel on Fire Suppression Costs. (2004) Large fire suppression costs-Strategies for cost management. Available online at:

https://www.forestsandrangelands.gov/resources/reports/documents/2004/cost management.pdf [verified 23 April 2018].

Sullivan AL, Ball R. (2012) Thermal decomposition and combustion chemistry of cellulosic biomass. *Atmospheric Environment*, 47, 133–41.

Swetnam TW, Betancourt JL. (1998) Mesoscale Disturbance and Ecological Response to Decadal Climatic Variability in the American Southwest, Journal of Climate, 11, 3128–3147.

Syphard, A.D., Keeley, J.E., Massada, A.B., Brennan, T.J., Radeloff, V.C. (2012) Housing Arrangement and Location Determine the Likelihood of Housing Loss Due to Wildfire. PLoS ONE 7(3): e33954.

Taylor SW, Wotton BM, Alexander ME, Dalrymple GN. (2004) Variation in wind and crown fire behaviour in a northern jack pine-black spruce forest. *Canadian Journal of Forest Research*, 34, 1561–76.

Theobald D.M. (2005) Landscape Patterns of Exurban Growth in the USA from 1980 to 2020. *Ecology and Society*, 10(1): 32.

Theobald D.M., Romme, W.H. (2007) Expansion of the US wildland-urban interface. *Landscape and Urban Planning*, 83, 340-354.

Thomas D.S., Butry, D.T. (2014) Areas of the U.S. wildland-urban interface threatened by wildfire during the 2001-2010 decade. *Natural Hazards*, 71, 1561-1585.

Trenberth, K. E., Dai, A., Rasmussen, R. M. & Parsons, D. B. (2003).The changing character of precipitation. *Bulletin of the American Meteorological Society*, 84, 1205–1217.

van Wagtendonk JW (2007) The history and evolution of wildland fire use. *Fire Ecology*, 3, 3–17. doi:10.4996/FIREECOLOGY.0302003

van Wagtendonk, JW, Fites-Kaufman J. (2006). Sierra Nevada bioregion in Sugihara NG, van Wagtendonk JW, Shaffer RE, Fites-Kaufman J, Thode AE, editors. Fire in California's ecosystems. University of California Press, Berkeley, California, USA.

Viegas DX, Bovio G, Ferreira A, Nosenzo A, Sol B (1999) Comparative study of various methods of fire danger evaluation in southern Europe. *International Journal of Wildland Fire*, 9, 235–246. doi:10.1071/ WF00015

Walding NG, Williams, HTP, McGarvie S, Belcher CM (2018). A comparison of the US National Fire Danger Rating System (NFDRS) with recorded fire occurrence and final fire size. *International Journal of Wildland Fire*, 27(2): 99-113. https://doi.org/10.1071/WF17030

Walding NG, Belcher CM. (*in prep*) Mapping future fire threats associated with climate-driven biome shifts in North America.

Weise DR, Hartford RA, Mahaffey L. (1998) Assessing live fuel moisture for fire management applications. Pages 49-55 in Teresa L. Pruden and Leonard A. Brennan (eds.). Fire in ecosystem management: shifting the paradigm from suppression to prescription. Tall Timbers Fire Ecology Conference Proceedings, No. 20. Tall Timbers Research Station, Tallahassee, FL.

Weise DR, Koo E, Zhou X, Mahalingam S, Morandini F, Balbi JH (2016) Fire spread in chaparral – a comparison of laboratory data and model predictions in burning live fuels, *International Journal of Wildland Fire*, 25, 980-994.

Westerling AL. (2016) Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring, *Philosophical Transactions Royal Society B*, 371 20150178. (http://dx.doi.org/10.1098/rstb.2015.0178)

Westerling AL, Gershunov A, Cayan D, Barnett T. (2002) Long lead statistical forecasts of area burned in western US wildfires by ecosystem province. *International Journal of Wildland Fire*, 11, 257–266. (doi:10.1071/WF02009)

Westerling AL, Gershunov A, Brown TJ, Cayan DR, Dettinger MD. (2003) Climate and Wildfire in the Western United States, *American Meteorological Society*, 595-604. (doi:10.1175/BAMS-84-5-595)

Westerling AL, Hidalgo HG, Cayan DR, Swetnam TW. (2006) Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity. *Science*, 313 (5789), 940-943.

Westerling, A.L., Bryant, B.P. (2008) Climate change and wildfire in California. *Climatic Change*, 87(1), S231–S249.

Westerling, A.L., Bryant, B.P., Preisler, H.K., Holmes, T.P., Hidalgo, H.G., Das, T., Shrestha, S.R. (2011) Climate change and growth scenarios for California Wildfire. *Climate Change*, 109(1), S445-S463.

Whitman E, Batllori E, Parisien MA, Miller C, Coop JD, Krawchuk MA, Chong GW, Haire SL. (2015) The climate space of fire regimes in north-western North America, *Journal of Biogeography*, 42, 1736-1749.

Wildland Fire Assessment System (2018a) Fire Weather Station Location. Available at https://www.wfas.net/index.php/fire-weather-stations-static-maps-43 [verified 13 May 2018]

Wildland Fire Assessment System (2018b) Processing. Available at https://www.wfas.net/index.php/processing-mainmenu-28 [verified 19 February 2018].

Wildland Fire Assessment System (2018c) Static Fuel Map. Available at https://www.wfas.net/index.php/nfdrs-fuel-model-static-maps-44 [verified 13 May 2018]

Wildland Fire Assessment System (2018d) Search the WFAS Archive. Available at https://www.wfas.net/index.php/search-archive-mainmenu-92 [verified 15 May 2018]

Wildland Fire Assessment System (2018e) Characteristics of a good fire danger rating system. Available at https://www.wfas.net/nfdrs2016/index.php/en/blog/characteristics-of-a-good-fire-danger-rating-system [verified 15 May 2018]

Wildland Fire Assessment System (2018f) National Fire Danger Rating System (NFDRS) Proposed Updates, Sept. 17, 2014. Available at https://www.wfas.net/nfdrs2016/index.php/en/nfdrs2016 [verified 15 May 2018]

Williams J. (2013) Exploring the onset of high-impact mega-fires through a forest land management prism. *Forest Ecology and Management*, 294, 4-10

Wisner, Ben, Piers Blaikie, Terry Cannon, and Ian Davis. 2004. At Risk: Natural Hazards, People's Vulnerability, and Disasters. New York: Routledge.


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